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Three Essays in the Economics of Food Marketing

Xun Li
xun.li@uconn.edu

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Xun Li, Ph.D.

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This dissertation consists of three empirical studies of food marketing, which directly and indirectly affects consumers' purchase behavior, reshapes their eating habit, and alters social welfare. Chapter one investigates the advertising spillover effects using the carbonated soft drinks market as a case study. In this chapter, spillover effects are modeled using the conventional linear and constant elasticity of substitution (CES) advertising production functions. Empirical results confirm strong and positive brand advertising spillover effects across brands belonging to the same company as well as negative spillover effects from advertising by competitors. Empirical results also indicate that the CES advertising production function outperforms the linear function, providing strong support for decreasing returns to scale in advertising and imperfect substitution between brand advertising

and advertising of other brands in the same company. Finally, the CES function results in significantly higher estimates of the price elasticities of demand as well as lower estimated markups.

Chapter two applies a stochastic frontier approach to rigorously ascertain the effects of food environment components on obesity outcomes. Using individual consumer data and food environment data from New England counties, empirical results indicate that supercenters and limited service restaurants are positively associated with weight outcomes, while fruit and vegetable stores and full-service restaurants are negatively linked to weight gain. In metropolitan counties, however, food environment factors that affecting weight outcomes are full-service restaurants and limited-service restaurants. In non-metropolitan counties, food environment components affect weight outcomes significantly only in counties adjacent to a metropolitan area. In counties that are not adjacent to a metropolitan area or which are completely rural, the associations between food environment components and weight outcome are consistently weak.

Chapter three contributes to the debate on food and energy prices by examining the relationship between milk and diesel prices and price pass-through. Empirical results indicate that energy price (e.g., diesel price) significantly impact the prices of milk products. The pass-through rates are around 0.6227. More interestingly, most of private labels have the lowest energy (diesel) pass-through rates, implying that comparing to other products, private labels are more invulnerable to energy price shocks.

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Xun Li

M.Sc. Agricultural and Resource Economics, University of Connecticut, USA, 2012

M.A. Economics, China University of Political Science and Law, Beijing, China, 2010

B.S., Finance and Mathematics, Wuhan University, Wuhan, China, 2008

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Three Essays in the Economics of Food Marketing

Presented by

Xun Li, M.Sc.,

Major Advisor

____

Dr. Rigoberto A. Lopez

Associate Advisor

____

Dr. Yizao Liu

Associate Advisor

____

Dr. Chad Cotti

University of Connecticut

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Chapter 1

Spillover Effects of TV Advertising: The Case of Carbonated Soft Drinks

1.1 Introduction

Although advertising can significantly affect consumer choices of food and beverage products (e.g., Zheng and Kaiser, 2008; Gao and Lee, 1995; Kaiser and Reberte, 1996; Kinnucan and Forker, 1998; Dharmasena, Kapps and Clauson, 2010; Tchumtchoua and Cotterill, 2010; Cohen and Rabinowitz, 2012; Bagwell, 2007), relatively few studies include it in empirical demand models of food and beverage products. Even when included, advertising spillover effects are typically analyzed at an aggregate sector level, such as U.S. non-alcoholic beverage industries (e.g., Zheng and Kaiser, 2008), or include generic advertising promoting an entire industry rather than specific brands. In the very limited brand-level studies of advertising spillover effects, one way to account for spillover effects of brand advertising is to consider a function that weights both brand and company advertising.[1] Previous studies include company as well as brand advertising and treat them as perfect substitutes by using a linear functional form, which also implies that advertising exhibits constant returns to scale, i.e., if advertising for

[1] Brand advertising is the advertising of a specific brand. Company advertising is advertising promoting all brands within the same company and is used herein as the advertising of other brands within a company. Spillover effects here refers to the phenomenon that brand advertising may have impacts on the demand for other brands that belong to the same company or to competitors.

each brand is doubled, its effect on brand demand is also doubled (e.g., Erdem and Sun, 2002; Balachander and Ghose, 2003). These underlying assumptions are contradictory to the likely existence of non-constant returns to scale in advertising.

According to Bagwell (2007), decreasing returns to scale may occur (1) as less responsive consumers are reached, or (2) as an increasing number of messages must be sent in order to reach a consumer that has not been exposed to advertising.[2] A number of empirical studies also offer evidence that advertising effectiveness is subject to diminishing returns. Thomas (1989) finds advertising diseconomies in the cigarette and soft drink industries, while Seldon, Jewell and O'Brien (2000) find them in the U.S. beer industry. When spillover effects of advertising are important, ignoring them or assuming constant returns to scale in advertising might lead to biased estimated price and/or advertising coefficients.

This article uses the carbonated soft drinks (CSDs) industry as a case study. Several features make this industry a relevant case to examine advertising spillover effects. First, CSD brands belonging to the same company can be clearly identified

[2] "Decreasing returns to scale" and "diminishing marginal returns" are two confusing concepts. The term "return to scale" arises in the context of a firm's production function. It denotes the quantitative change in output of a firm or industry resulting from a proportionate increase in all inputs. The term "decreasing marginal returns" means that the productivity of a variable input declines as more is used in short-run production. As Simon and Arndt (1980) mention, when discussing advertising quantities, writers inevitably have in mind an increase in advertising alone. Here we consider the advertising as the only input, so decreasing returns to scale and the decreasing marginal returns are similar. Here we follow Bagwell (2007) and use the term "decreasing returns to scale."

and spillover effects measured.[3] Second, the major CSD manufacturers (Coca Cola, PepsiCo and Dr. Pepper) emphasize non-price competition such as advertising, highlighting the importance of appropriately modeling the effects of advertising on consumer choices. Third, CSDs are the most heavily advertised beverage products in the United States. The Coca Cola Company spent $267 million in 2010, competing with PepsiCo's $154 million and Dr. Pepper's $104 million (Zmuda, 2011). Last but not least, CSDs lead the beverage category and have been identified as the primary contributor of calories in the ongoing obesity epidemic (Vartanian, Schwartz and Brownell, 2007; Pereira, 2006; Malik, Schulze and Hu, 2006; Brownell et al., 2009; Marriott et al, 2010; Johnson and Yon, 2010; Lopez and Fantuzzi, 2012). According to Zmuda (2011), in 2010 the average American drank 45 gallons of CSDs per year. Thus, understanding how consumption is affected by advertising can serve as a basis for policies aimed at regulating advertising of CSDs (e.g., Seidman, 2011), as is done in France, Denmark and Sweden (IACFO, 2003), or regulating advertising of fast foods, as in Canada (Dhar and Baylis, 2011).

This article contributes to the advertising literature by measuring and testing for the degree of advertising spillover effects through nesting brand and company

[3] A maintained assumption in this article is that the consumer is fully aware of what manufacturer brands belong to each of the three major companies. While identifying companies is obvious when the brand name contains the company name (e.g., Coke Zero), some consumers may not link brand names that do not contain the company name (e.g., Mountain Dew, which belongs to PepsiCo). However, the leading brands of each company do contain the company name in the brand name and are the heaviest users of TV advertising.

advertising via a constant elasticity of substitution (CES) advertising production function. It is the first to apply a CES production function to advertising. The results for the CSD market indicate that brand advertising has a positive and significant impact on the demand for all brands belonging to the same company, thereby "lifting all boats" within a company. As in previous studies, we find that competitors' advertising has a negative and significant impact on demand for CSDs of a given firm. Moreover, the CES advertising function outperforms the conventional linear form, providing strong evidence of decreasing returns to scale in advertising and, therefore, of imperfect substitution between brand and company advertising, rejecting the common assumption of a linear advertising production function. Finally, the CES function results in significantly lower price elasticity of demand and estimated markups.

1.2 Empirical Strategy

1.2.1 The Demand Side

For the purpose of this article, consumers are assumed to choose a CSD brand in two steps. First, they choose a CSD company (or an outside good) and then a specific CSD brand within that company.[4] There are G companies which are regarded as clusters or "groups" of brands facing consumers. Following Berry (1994) and Kusuda (2011), the utility of consumer i from choosing one unit of product $j \in g$ $(g = 1,2, \dots G)$ is assumed to be:

$$U_{ij} = \delta_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij}, \qquad 1.2.1$$

where $\delta_j = X_j{}'\beta - \alpha P_j + \xi_j$ is the mean of the utility. X_j is a vector of observable product characteristics, P_j is the price of product j. ξ_j is the utility shocks observed by the consumer but not the researcher. The second component ζ_{ig} is common to all products in group g and $\epsilon_{ij} \sim i.i.d.$ extreme value. Parameter σ is between zero and one, determining the within-group correlation of utility levels. As σ approaches one, the within-group correlation of the utility level goes to one, and as σ approaches zero, the within-group correlation goes to zero. Based on Cardell (1997), $\zeta_{ig} + (1-\sigma)\epsilon_{ij}$ is an extreme value random variable.

[4] Alternative paradigms could include grouping CSDs by selected characteristics such as calorie content (diet vs. regular) or flavor (e.g., Lime Sprite vs. 7 Up). Given our interest in company advertising spillover effect, we consider companies as clusters. In our model, the effects of similarity of characteristics are captured by including the brand-specific characteristics.

The market share of brand j in group g is given by

$$s_{j/g} = \frac{exp(\frac{\delta_j}{1-\sigma})}{\sum_{j \in g} exp(\frac{\delta_j}{1-\sigma})}, \qquad 1.2.2$$

and the probability of choosing one of the group g products (the group share) is

$$s_g = \frac{D_g^{(1-\sigma)}}{\sum_g D_g^{(1-\sigma)}}, \qquad 1.2.3$$

where $D_g = \sum_{j \in g} exp\left(\frac{\delta_j}{1-\sigma}\right)$. Thus, the market share of brand j can be simply expressed as

$$s_j = s_{j/g} s_g . \qquad 1.2.4$$

Normalizing the utility for the outside good to zero, the nested logit model is

$$ln(s_{jt}) - ln\,(s_{0t}) = X_j{}'\beta - \alpha P_j + \sigma ln(s_{j/g,t}) + \xi_{jt}. \qquad 1.2.5$$

Following Dubé, Hitsch and Manchanda (2005), advertising is modeled as a goodwill stock in order to capture the carry-over effects of advertising's impact on demand. Advertising goodwill GW_{jt} for CSD brand j in time period t is given by

$$GW_{jt} = \sum_{n=0}^{\infty} \lambda^n\, \Psi(A_{jt-n}), \qquad 1.2.6$$

where $\Psi(\cdot)$ is a function of current and past advertising, A_{jt} represents advertising for product j in time period t, and $\lambda \epsilon (0,1)$ is a geometric decay parameter.[5] The advertising aggregator is defined as

$$\Psi(\cdot) = \begin{cases} log(1 + A)\,, if\ A > 0; \\ 0, \text{otherwise.} \end{cases} \qquad 1.2.7$$

A linear advertising production function is given by $AD_{jt} = \Phi GW_{jt} + \varphi GW_{-jt}$, where the first term denotes brand advertising and the second term denotes advertising of other brands belonging to the same company. Note regarding the spillover effects parameter $\varphi \geq 0$ that where $\varphi = 0$ no spillover effect is indicated. A CES advertising production function[6] is given by:

$$AD_{jt} = (\Phi GW_{jt}{}^{\rho} + \varphi GW_{-jt}{}^{\rho}\,)^{k/\rho}\,, \qquad 1.2.8$$

where $\rho = \frac{\gamma - 1}{\gamma}$ and γ is the elasticity of substitution. k measures returns to scale, and when $k > 1$ or $k < 1$, advertising has corresponding increasing or decreasing returns to scale. When $k = 1$ and $\rho = 1$, the CES advertising production function collapses to the linear form. Competitors' advertising is obtained by aggregating the goodwill of the brands belonging to them, given by

$$AD_{com} = \sum_{h \notin g} GW_{ht}, \qquad 1.2.9$$

[5] Note that at this point, we are leaving open the empirical definition of A (e.g., expenditure or exposure).
[6] Note that AD_{jt} is total advertising effect brought by brand advertising and company advertising, and is different from A_{jt}. Equation (8) is generalized.

where h denotes brands not belonging to firm g. Incorporating (8) and (9) into (5), the estimating model becomes:

$$lns_{jt} - lns_{0t} = X_j'\beta - \alpha P_j + \left(\Phi GW_{jt}{}^{\rho} + \varphi GW_{-jt}{}^{\rho}\right)^{k/\rho} + \pi\, AD_{com} +$$

$$\sigma\, ln\left(s_{j/g,t}\right) + \xi_{jt}, \qquad 1.2.10$$

where π is the coefficient for the advertising spillover effect from competitors.

When brands j and l belong to group g, the own- and cross-price elasticity of demand of brand j are, respectively:

$$\eta_{jj} = \frac{-\alpha}{1-\sigma} P_j + \frac{\alpha}{1-\sigma} s_{j/g} P_j - \alpha\left(1 - s_g\right) s_{j/g} P_j\,, \qquad 1.2.11$$

and

$$\eta_{jl} = \frac{\alpha}{1-\sigma} s_{l/g} P_l - \alpha\left(1 - s_g\right) s_{l/g} P_l\,, \qquad 1.2.12$$

while when brands j and l are in different groups, the cross-price elasticity is given by:

$$\eta_{jl} = \alpha s_g s_{l/g} P_l\,. \qquad 1.2.13$$

An increase of brand l's advertising level will directly increase the demand for itself and decrease the demand for all other brands (business-stealing effect or cannibalism), which can be measured by

$$\chi_{rl} = \frac{\partial s_r}{\partial Ad_l}\frac{Ad_l}{s_r}, \qquad 1.2.14$$

where $\chi_{rl} > 0$ if $r = l$ and $\chi_{rl} < 0$ if $r \neq l$, and r denotes any brand. Second, the increase of brand l's advertising level ($l \in g$) will increase the total advertising output for the whole company, which will in turn affect the demand of brand j (spillover effect), which is denoted as

$$\chi_{jl} = \frac{\partial s_j}{\partial \sum_{l \neq j, l \in g} Ad_l}\frac{\partial \sum_{l \neq j, l \in g} Ad_l}{\partial Ad_l}\frac{Ad_l}{s_j}. \qquad 1.2.15$$

Third, the competitive effect (i.e., the effect on the demand for brand h, in another group ($h \in g'$) can be measured by

$$\chi_{hl} = \frac{\partial s_h}{\partial \sum_{l \notin g'} Ad_l}\frac{\partial \sum_{l \notin g'} Ad_l}{\partial Ad_l}\frac{Ad_l}{s_h}. \qquad 1.2.16$$

1.2.2 Markups

A representative firm f maximizes the aggregated profits across all its brands, $\mathcal{B}$. The firm takes prices and advertising levels of all other firms' brands as given when it sets prices and advertising level for its own brands. The profit maximization problem is

$$Max \sum_{j \in \mathcal{B}} (p_j - mc_j) M s_j(p_j;\, ad_j) - c_f, \qquad 1.2.17$$

where p_j is price for brand j, M is market size, mc_j is marginal cost for brand j, and c_f is the fixed production costs of firm f. The first-order condition with respect to price for brand j is

$$s_j(p_j;\ ad_j) + \sum_{r \in \mathcal{B}} (p_r - mc_r) \frac{\partial s_r(p_r;\, ad_r)}{\partial P_j} = 0. \qquad 1.2.18$$

Following Berry (1994), differentiating the market share equation (4) with respect to the mean utility for brand j yields

$$\frac{\partial s_j}{\partial \delta_j} = \frac{1}{1-\sigma} s_j [1 - \sigma s_{j/g} - (1-\sigma) s_j], \qquad 1.2.19$$

Thus, from $\frac{\partial s_j}{\partial p_j} = \frac{\partial s_j}{\partial \delta_j} \frac{\partial \delta_j}{\partial P_j}$ and equation (19), the price-cost markup at equilibrium is given by

$$p_j - mc_j = \frac{1-\sigma}{[1 - \sigma s_{j/g} - (1-\sigma) s_j] \alpha}\,. \qquad 1.2.20$$

To assess the implications of spillover effects, we estimate the model under a linear and a CES advertising production function and compare the price and advertising elasticities and price cost margins as well as statistical performance.

1.3 Data

To estimate the demand model, we combine two Nielsen datasets, both obtained from the Zwick Center for Food and Resource Policy at the University of Connecticut. One is the Homescan dataset depicting households' brand-level CSD purchases in grocery stores, drug stores, vending machines, and online shopping sites in 9 designated market areas (DMAs) on a weekly basis from February 2006 to December 2008.[7] The records of the Homescan dataset include information on product characteristics (e.g., package size and name of brand), marketing (e.g., unit price and promotion displays), location and time of each purchase, and household demographics. The second dataset is television advertising consisting of weekly brand-level Gross Rating Points (GRPs) from national (cable, network and syndicated) and local (spot) television advertising for each DMA.[8] These two datasets are combined at the bi-weekly level, directly linking TV brand advertising exposure to CSD purchases. Since Dubé, Hitsch and Manchanda (2005) report an estimated advertising decay parameter of 0.89 with weekly data, here a decay parameter of 0.79 (i.e., 0.89^2) is used for bi-weekly data. Data for the prices of

[7] A designated market area (DMA) is a geographic area defined by Nielsen Media Research Company as a group of counties that make up a particular market. These counties comprise the major viewing audience for the television stations located in their particular metropolitan area. The areas do not overlap, and every county in the United States belongs to only one DMA. The DMAs in this article are New York, Detroit, Boston, Washington DC, Atlanta, Chicago, Houston, Los Angeles and Seattle.

[8] Gross ratings points are a commonly used measure of advertising exposure (A_{jt} in equation (6)). They are calculated as the percentage of the targeted audience that views an advertisement times the frequency.

aluminum and electricity inputs are, respectively, from the Index Mundi (2012) and the U.S. Energy Information Administration (2008).[9]

The market share is computed based on the potential market size, which is defined as combined per capita consumption (in gallons) of the top 14 CSDs plus the outside good (juices, milk and other CSDs) times population for each period and DMA. Following convention, each DMA and time period combination is treated as a separate market, resulting in 684 markets (9 DMAs x 76 bi-weekly periods).

Since each of the 14 CSD brands are observed in each market, we end up with 9,576 market-level observations (14 times 684). Product characteristics include price, nutritional characteristics, and television advertising. Sugar, sodium and caffeine content are key nutritional indicators that affect CSD choices (Lopez and Fantuzzi, 2012). Table 1 lists CSD brands and product attributes for 14 leading CSDs from three companies (Coca Cola, PepsiCo, and Dr. Pepper) and provides summary statistics for them as well as their market shares, prices and TV advertising GRPs, which are averaged across the nine DMAs and the 76 bi-weekly periods. Coke Classic Regular, Pepsi Regular and Dr. Pepper Regular are the most popular among brands of the company they belong to, with market shares of 5.17%,

[9] Index Mundi is a platform containing various data concerning selected attributes and characteristics of counties, including detailed county statistics, charts and maps compiled from multiple sources.

4.56% and 1.49%, respectively. Correspondingly in the advertising levels (194.3, 180.0 and 192.9, respectively), are also top within their company brands.

Figure 1 illustrates the pattern of GRPs in Boston for the two leading soda brands, Coke Regular and Pepsi Regular.[10] For Coke Regular, the largest peak for advertising happened during the August 2008 Olympics. Roughly speaking, the fluctuation of advertising for the two brands follows the pattern that one brand hits the bottom when the other reaches the peak, although the variation of advertising for Coke Regular is more exaggerated.

1.4 Estimation and Results

Following Berry (1994), price and within-group market share are regarded as endogenous variables since retailer prices and within-group market shares depend on unobserved product and consumer characteristics. Advertising is also potentially endogenous because it might correlate with some unobservable company strategies that will affect demand. To eliminate potential biases due to endogeneity, a set of instrumental variables is used in the identification procedure including product nutritional characteristics, input cost variables (such as the price of aluminum, price of electricity and average price of advertising), DMA dummies,

[10] Here we use Boston as an example since other cities show similar patterns.

and seasonal dummies. In addition, Hausman-type instruments (Hausman, 1994), such as average within-group market share and average advertising level in other cities, are also used. The Sargan's test and first stage F-stats are used to test whether the instrumental variables are valid and relatively strong. The Durbin statistic (1954) is applied to test endogeneity of the variables. After estimation, the model specifications are compared via values of the root mean square percentage error (RMSPE). A smaller RMSPE indicates a better fit of the model (Vu, Hammes and Im, 2012).

The two-stage least squares (2SLS) approach is applied for the linear advertising model and the two-stage residual inclusion (2SRI) approach for the CES model. The 2SRI estimator has been shown to provide more consistent estimates than two-stage predictor substitution (2SPS) in nonlinear models (Terza, Basu and Rathouz, 2007). The results are presented in the following section.

Table 2 presents the estimation results from three model specifications: (1) excluding company advertising and competitors' advertising (no spillover effects); (2) with spillover effects, using a linear advertising function form; and (3) with spillover effects, using a CES advertising function form. The Durbin statistic validates that price, advertising and within-group market share are endogenous. The Sargan's test results and the first stage F-stats indicate that the instrumental variables are valid and relatively strong. Values of the RMSPE indicate that model

3 outperforms model 2, and that model 2 is a better fit when compared to model 1. Overall, the preferred model is 3 using the CES advertising production function.[11]

Nearly all key parameter estimates in Table 2 are highly statistically significant and all have the expected signs. Consumers have a negative response to price (-2.683) and a positive response to both brand advertising (0.249) and company advertising (0.745), which highlights the importance of including company advertising to account for spillover effects. It is interesting to note that the price (and non-advertising) coefficients in models 1 and 2 are not significantly different. This implies that simply including advertising in a linear production function model (model 2) leads to similar price and non-advertising coefficients as using a demand model that does not include advertising at all (model 1). However, both price coefficients are significantly smaller (by nearly 40%) in absolute value than the estimated price coefficients using the CES advertising form (model 3). Thus, the CES model shows greater price responsiveness and, therefore, more price-elastic demands. The dramatically different estimates of price coefficients under linear vs. CES advertising models (-1.93 vs. -2.683) highlight the importance of appropriate model specification for advertising spillover effects, particularly when price policy instruments (e.g., taxes) are being considered. In addition, stark

[11] We also checked model 3 for robustness. First, the CES was compared to a Cobb-Douglas specification of advertising production and, based on the root mean square percentage error, the CES significantly outperformed the Cobb-Douglas form. Second, the result was also robust to alternative lags of GRPs in the computation of advertising goodwill.

differences are also apparent for all non-advertising coefficients. Table 2 also shows that the CES specification leads to significantly greater responsiveness to brand and company advertising, meaning that a linear form would also lead to underestimation of the impacts of advertising on demand.

As expected from previous work, competitors' advertising has a negative impact on demand. The magnitude of that result is robust across the linear and CES specifications. The CES advertising function shows a strong degree of decreasing returns to scale. The elasticity of substitution parameter indicates brand and company advertising are far from being perfect substitutes. Moreover, the estimated within-group heterogeneity parameter indicates that consumers' utilities are highly correlated for brands within a company.

Predicting the market share is important for a company's marketing strategy, and Table 2 also illustrates the predictive power of the three model specifications. To create out-of-sample predictions, the three models are estimated with data from the first 71 biweekly-periods and then used to predict market shares in the last 5 periods. In Table 2, the out-of-sample mean squared errors (MSE) are reported following Dubé (2004). The MSE value of model 3 is the smallest, indicating that including advertising spillover effects in a CES function has the best predictive power.

Table 3 reports average own-price elasticities and cross-price elasticities under alternative advertising models, averaged over all 684 markets.[12] Note that model 3, which accounts for brand and company advertising using a CES function, produces higher own-price elasticities of demand. In fact, the CES model produces price elasticities that better align with those estimated in previous studies. For example, Dubé (2004) reports the elasticity in the -2 to -3.6 range for specific sizes and brands of CSDs; Dhar et al. (2005) reports them between -2.7 and -4.4, and Chan (2006) reports own-price elasticity for CSDs at household level are between -5 and -11. It is worth noting that in each nest, the elasticity of the most popular brand is significantly lower than the elasticities of less popular brands. Between groups, the elasticity of brands within the relatively popular company is generally lower than within the least popular group (e.g., Coca-Cola Company vs. Dr. Pepper Company). In addition, all the cross-price elasticities are positive, indicating that all of these brands are, to some extent, substituted. For example, for Coke Regular, the price changes of the other three brands in Coca-Cola Company positively impact the demand of Coke Regular. The impact from Coke Diet is largest. One possible explanation is that Coke Diet is more similar in brand identity to Coke Diet compared with Sprite Regular and Coke Zero. Very similar patterns are found in other companies' products.

[12] For simplicity, we report only the own-price elasticities of demand.

Table 4 presents the average advertising elasticities of demand for all three models. All the own-advertising elasticities are less than one. The own-advertising elasticities calculated based on model 3 are lower than those based on the other two models, especially for the most popular brands (e.g., Coke Regular, Pepsi Regular and Dr. Pepper Regular). In models 1 and 2, the own-advertising elasticity of the most popular brand is significantly lower than the elasticities of less popular brands (e.g., Coke Regular vs. Dr. Pepper Regular or Coke Regular vs. Coke Diet). These findings are consistent with Dubé (2004). However, in model 3, all the own advertising elasticities are of similar magnitude and around 0.25. It is worth noting that the two models (2 and 3) that include spillovers of brands within the same company result in positive cross-price elasticities of advertising indicating that the spillover effect dominates the cannibalism effects of brand advertising within the same company. At the same time, when including spillover effects, the impact on sales of competing company brands is estimated to be larger than when spillover effects are ignored in the model.

In addition, according to the Dorfman-Steiner rule (Dorfman and Steiner, 1954), these results suggest an optimal advertising-sales ratio of about 9 percent for the 14 brands taken as a whole. The estimates are also consistent with Basmann's adding up condition (Basmann, 1956), which intuitively states that if advertising is effective at increasing demand for the advertised product, it must also decrease demand for some other products.

Table 5 reports the estimated price-cost markups and Lerner Indexes for each brand. The models are consistent that Coke Diet has the largest degree of and Mountain Dew Regular the smallest degree of market power. Note that model 3 produces significantly lower markups and Lerner Indexes, which is consistent with higher estimated price elasticities of demand. The Lerner Index estimates based on model 2 range from 0.181 to 0.330, and those based on model 3 from 0.106 to 0.195.[13]

These findings imply the importance of properly modeling advertising in demand models. For example, Berning (2011) points out that because brand advertising can affect the price elasticities of demand, excluding it from the model can lead to misleading estimated impacts of simulating taxes on CSDs, particularly under 100% pass-through rates. Second, given the growing problem of obesity and especially childhood obesity, governments are considering a variety of policy solutions, including banning advertisements of so-called unhealthy food and beverages. An example is the Children's Food and Beverage Advertising Initiative (CFBAI) (Better Business Bureaus, 2014). However, there has been concern that

[13] Tollison, Kaplan and Higgins (1991) report that the profit margin of the Coca Cola Company was 0.124; Dubé (2005) reports the margin for Coke Classic 12 packs, for example, as 0.433; Dhar et al. (2005) report the Lerner Index for Coke within a Bertrand game as 0.26; and Deichert et al. (2006) report the profit margin of Coca-Cola Company as 0.22.

this recent voluntary agreements to restrict advertising is not working well (Kunkel, McKinley and Wright, 2009). One reason could be the spillover effects of advertising (Berning and McCullough, 2013). If policy only curtails the advertising of some brands, CSD consumption cannot be cut to the expected level due to the existence of advertising spillover effects from other brands belonging to the same company.

1.5 Conclusions

This article confirms that company advertising as well as brand advertising is a significant shifter of demand at the brand level. Thus, to properly account for the impact of advertising on consumer choices, empirical work should incorporate not only brand advertising but also company advertising, as the latter is a "rising tide that lifts all boats" in a company's product portfolio. However, these effects can be characterized in two ways. One is that there is a significant degree of decreasing returns to scale in advertising; the other is that brand and company advertising are quite far from being perfect substitutes. If properly modeled, company spillover effects due to high correlation of consumer association of brands within the same company point to brand advertising spillover effects on company-wide demand has nearly equally important. From a modeling standpoint, a CES advertising production function outperforms the linear form as well as excluding advertising in the demand model altogether. It also leads to significantly higher estimated price elasticities of demand and lower price-cost markups, indicating a more competitive pricing behavior.

Two avenues for future research seem fruitful. Whereas this article focuses primarily on demand effects, one is to extend the model by endogenizing advertising decisions in the context of a portfolio. It is important, for instance, to include modeling the supply side of the market, as induced price changes can have an important bearing on the direct and spillover effects of advertising. Further work might also consider social media, which are increasingly used as a substitute for traditional advertising by the CSD and other beverage and food industries.

Chapter 2

Food Environment and Weight Outcomes: A Stochastic Frontier Approach

2.1 Introduction

Obesity in the United States has been increasingly cited as a major health issues in recent decades. In 2010, approximately 36% of American adults and 17% of children were obese (Ogden et al., 2012). A substantial volume of previous work has focused on the obesity epidemic and the effectiveness of policy interventions to curb its incidence. In addition to factors such as individual socio-demographics (including income, age, race, number of children, gender, etc.), behavioral characteristics (e.g., smoking, drinking, etc.) and socio-economic factors (e.g., labor market conditions, economic recessions and peer effects), food environment is receiving increasing attention.

Food environment is defined by the National Cancer Institute (2013) to include “food stores, restaurants, schools and worksites.” Similarly, McKinnon et al. (2009) categorized the food environment as the “food store environment (e.g., grocery stores, supermarkets, specialty food stores, farmers’ markets, and food pantries); restaurant food environment (e.g., fast food and full-service restaurants); school food environment (e.g., cafeterias, vending machines, and snack shops in daycare settings, schools and/or colleges); and/or worksite food environment (e.g., cafeterias, vending machines, snack shops)." The USDA (2013a) defines food environment factors as store/restaurant proximity, food prices, food and nutrition assistance programs, and community characteristics as they interact to influence food choices and diet quality. This paper emphasizes the availability of food outlets of different industrial categories. Following Bonanno and Goetz (2010), food outlets are categorized in this paper by industry definitions, which include supermarkets and other grocery stores, convenience stores, fruit and vegetable markets, warehouse clubs and supercenters, full-service restaurants and limited-service eating places.

Supermarkets generally offer high-quality and low-cost food (Powell et al, 2007). Morland,Diez Roux and Wing (2006) report that the presence of supermarkets is associated with a lower prevalence of obesity and overweight. As for grocery stores, Chen et al. (2010) find that the effect of improvements in access to chain grocers on body mass index (BMI) varies depending on community characteristics. More specifically, increasing access to chain grocers in low-income communities decreased the average BMI for all respondents by approximately 0.3 points.

Convenience stores are generally regarded as posing an increased risk of obesity since they generally offer less variety, higher prices and lower quality produce than supermarkets (Zenk and Powell, 2008). For example, Morland et al.

(2006) find that convenience stores are positively associated with a higher prevalence of obesity and overweight.

Fruit and vegetable markets as well as local agriculture are also documented as factors that impact weight outcomes. By examining the diet of school-aged children and adults, Lin and Morrison (2002) provide evidence that consuming fruit and vegetables decreases BMI. Berning (2012) shows that access to local agriculture (farmers' markets and community supported agriculture) is negatively associated with weight gain.

Warehouse clubs and supercenters are also linked with the prevalence of obesity. Using data from the Behavior Risk Factor Surveillance Survey (BRFSS) matched with Wal-Mart Supercenter entry dates and locations, Courtemanche and Carden (2010) find that the density of Wal-Mart Supercenters is positively correlated with obesity rates.

Full-service restaurants are generally regarded as serving healthier foods. However, the role of full-service restaurants is still controversial. Some researchers find evidence that full-service restaurants are associated with lower weight status. For example, Mehta and Chang (2008) analyze the relationship between a restaurant environment and weight status across counties in the United States, finding a negative association between availability of full-service restaurants and the prevalence of overweight and obesity. However, some researchers, for example Powell and Nguyen (2013), find that full-service restaurant consumption is associated with a net increase in daily total energy intake of 160 kcal for children and 267 kcal for adolescents. They conclude that full-service restaurant consumption is associated with higher net total energy intake and poorer diet quality.

Other studies find that access to low-quality food away from home, particularly from fast-food restaurants, has a positive effect on obesity rates. For example, Chou, Grossman and Saffer (2004), combining state-level data with individual demographic and weight data from the BRFSS, present evidence that the per capita number of fast-food restaurants positively affects rates of obesity. Currie et al. (2010) find that an increase in fast-food restaurants leads to an increase in obesity and weight gains among ninth-graders and pregnant mothers. Dunn (2010) employs an identification strategy based on county-level variation in the number of fast-food restaurants and shows that their availability is correlated with increased BMI among females, and among non-whites in counties with medium population density. However, Anderson and Matsa (2011), using food-intake micro data and correcting for endogenous location of establishments, find no causal link between food consumption at restaurants (both fast-food and full-service restaurants) and obesity.

Previous work has focused on the impact of different aspects (e.g., outlets) of the food environment on weight outcomes. However, a comprehensive study of the relationship between food environment and weight gain is lacking. The omission of an analysis that comprehensively includes various components of food environment can lead to not only biased results but also disallow a direct comparison of the importance of different determinants of weight outcomes. Comprehensively measuring the impact of the food environment on weight outcomes requires an integrated framework that accounts not only for food environment factors but also for consumer characteristics.

This paper applies a stochastic frontier approach (SFA) to extend the health production function development by Grossman (1972), using BMI as output, based on consumers' demographics and behavioral characteristics and treating food environmental factors as determinants of deviations from the frontier. The food environment can affect weight outcomes in different ways. First, food environments can affect food-access costs. In general, people living in poor food environments need to pay more (e.g., time, transportation costs) to obtain food. The diversion of resources into unproductive uses leads to inefficiency (Collier, 1999). Second, different food environments imply different availability of types of food (e.g., healthy and unhealthy) in consumers' choice set. In poor food environments, healthy foods are fewer so that consumers' choices are bounded and they cannot allocate limited resources efficiently. Third, in the long run, the food environment might reshape people's eating styles and habits, leading to inefficiency. For example, there is evidence from medical research that the nutrients in fast food are inherently addictive (Colantuoni et al., 2002; Grigson, 2002; Del Parigi et al., 2003).

Using New England data at the county level, our empirical results indicate that supercenters and limited-service restaurants are positively associated with weight outcomes, while fruit and vegetables store and full-service restaurants are negatively linked to weight gain. In metropolitan counties, food environment factors affecting weight outcomes are full-service restaurants and limited-service restaurants. In non-metropolitan counties, food environment components affect weight outcomes significantly only in counties adjacent to a metropolitan area. In counties that are not adjacent to a metropolitan area or which are completely rural, the associations between food environment components and weight outcome are consistently week. In addition, this paper evaluates the BMI production "efficiency" associated with different aspects of food environment, ranks them by counties, and suggests policy implications.

2.2 Empirical Strategy

The empirical framework relies on a stochastic production function and an equation for the determinants of inefficiency, where the explanatory variables of the inefficiency term include food environment indicators. Adapting the health production function proposed by Grossman (1972), a stochastic frontier health production function with technology inefficiency is given as:

$$H = H(X, Z)\, exp(v)\, exp(-u), \qquad 2.2.1$$

where H is the health status, X is inputs, including demographic characteristics such as age, education, race, income, gender, and behaviors such as drinking and smoking, and Z stands for the fixed effects of location and time. v is the unobservable individual characteristics that make the production frontier stochastic. u is non-negative random variables, associated with technical inefficiency of health production. The production function $H(X, Z)$ is deterministic output, given input combinations.

$H(X, Z)$ is assumed to take a Cobb-Douglas form. Taking the logarithm of both sides, the empirical model is given by:

$$y_{ik} = x_i'\beta + v_{ik} - u_{ik} \qquad 2.2.2$$

where subscript i, k denotes individual consumer i in food environment k. y_{ik} is the log measure of health outcome; x_i denotes the log of consumer characteristics; v_{ik} is a random symmetric disturbance accounting for noise assumed to be independently, identically distributed with a mean of zero and variance σ_v^2; u_{ik} is an asymmetric error term that accounts for systematic deviations from the frontier due to food environment factors where individual i resides.

Given that weight gain is associated with negative health outcomes such as type II diabetes, hypertension, cardiovascular disease and disability, the empirical model in (2) can be expressed as:

$$logBMI_{ik} = x_i'\beta + v_{ik} + \tilde{u}_{ik}, \qquad 2.2.3$$

Figure 1 illustrates equation (3). The deviation from the deterministic frontier can be decomposed into two effects: noise effect (v_{ik}) and inefficiency effect ($\tilde{u}_{ik}$). If there is no inefficiency effect, the BMI outcomes lie at the point (X_A, Y_A^*) or (X_B, Y_B^*), which are ideal levels of BMI outcomes. With inefficiency brought about by food environments and other social-economic factors, the observation points of BMI outcome level are (X_A, Y_A) or (X_B, Y_B).

Here, the BMI production efficiency index is defined as $\exp(-\tilde{u}_{ik})$ (Farrell, 1957). A higher efficiency index of BMI production indicates one can produce BMI closer to the ideal level. A higher value of $\tilde{u}_{ik}$ indicates a higher BMI level above the ideal level and a lower BMI production efficiency (equivalently, higher BMI product inefficiency) and thus, higher health risks.

This paper follows Battese and Coelli (1993), who estimated a stochastic frontier model incorporating a technical inefficiency term that is a linear function of several factors. Specifically, the following function is estimated along with the production function in (3):

$$\tilde{u}_{ik} = z'_{ik}\delta + \omega_{ik}, \qquad 2.2.4$$

where z'_{ik} denotes a set of indicators for food environment and other social-economic factors, δ is a corresponding vector of parameters, and ω_{ik} is a random error that distributes independently of v_{ik} and follows a truncated normal distribution with a zero mean and variance σ_u^2, with truncation point at $-z'_{ik}\delta$, i.e., $w_{ik} \geq -z'_{ik}\delta$. In this study, components of food environment, such as the density of food stores and restaurants, are included in explanatory variable z_{ik} to test whether the food environment causes inefficiency for BMI production.

2.3 Data

Table 1 presents the definitions and descriptive statistics of county-level variables and individual-level variables. It shows that the densities of full-service restaurant and limited-service restaurant are much higher (0.954 and 0.939, respectively) than those of other food environment components. Average BMI (26.502) with standard deviation (5.026) indicates that being overweight is common in New England. The main data source we used to estimate the model is the BRFSS annual survey data from the Centers for Disease Control and Prevention during 2001-2010. This survey consists of a self-reported response of more than 350,000 consumers throughout the United States, and provides data on body mass index (BMI) and consumer characteristics and on health care, risky behaviors, disease prevalence and preventive health practices. Individuals with a BMI below 12 or above 90 are omitted as a standard practice, and only individuals between 18 and 75 years old are included in this analysis (Dunn, 2010). In addition, pregnant women and individuals who reported "disabled" as their employment status are omitted from this analysis.

To obtain indicators of the food environment, we grouped the individual observations by county and matched them with data from the U.S. Bureau of the Census (USBC), County Business Patterns for 2001-2010 to include the number of establishments in the following industries: supermarkets and other grocery stores (NAICS 44511), convenience stores (NAICS 44512), warehouse clubs and supercenters (NAICS 45291), fruit and vegetables stores (NAICS 44523), full-service restaurants (NAICS 72210), and limited-service eating places (NAICS

72211). 14 Following Dunn (2010) and Courtemanche and Carden (2010), we use numbers of food outlets per 1000 persons to approximate availability. Normalizing by population implicitly assumes that all food outlets and population are uniformly distributed across a county. The population data used in this paper are from USCB Population Estimates Program.

Other data sets used in this paper including median income, crime rates (including violent crime and property crime) are respectively from USBC Small Area Income and Poverty Program estimates and U.S. Department of Justice Uniform Crime Reporting Statistics. The numbers of highway exits are collected from Wikipedia. Other information like square miles of land in each county, is taken from the USCB Gazetteer of Counties.

[14] According to the definition from U.S. Bureau of Census (USBC), NAICS 44511 comprises establishments generally known as supermarket and grocery stores primarily engaged in retailing a general line of food, such as canned and frozen foods, fresh fruits and vegetables, and fresh and prepared meats, fish and poultry. NAICS 44512 comprises establishments known as convenience stores or food marts (except those with fuel pumps) primarily engaged in retailing a limited line of goods that generally include milk, bread, soda and snacks. The establishments in industry NAICS 44523 are primarily engaged in retailing fruits and vegetables via electronic home shopping, mail-order, or direct sales, and growing and selling vegetables and or fruits at roadside stands. NAICS 45291 includes warehouse clubs and supercenters primarily engaged in retailing a general line of groceries in combination with general lines of new merchandise, such as apparel, furniture, and appliances. The establishments in industry NAICS 72211 are primarily engaged in providing food services to patrons who order and are served while seated and who pay after eating. The industry NAICS 72221 comprises establishments primarily engaged in providing food services where patrons generally order or select items and pay before eating; most of these establishments do not have waiter/waitress service, but some provide limited service, such as cooking to order (i.e., per special request), bringing food to seated customers, or providing off-site delivery.

2.4 Estimation and Results

Since the respondents in the BRFSS survey data are not the same over time, the data structure is not a panel. Therefore, observations are pooled. The availability of food outlets is potentially endogenous, arising from two sources. One is the correlation between the availability of food outlets and unobservable individual characteristics. For instance, an individual's eating habits, health consciousness and demand for food might affect his/her BMI level as well as the presence of food outlets. The other is the correlation between the density of food outlets and county characteristics. For example, food outlet establishments are more likely to enter counties where there is a better environment and lower crime rate, which also affect weight outcomes. [15]

To account for endogeneity, this paper follows Dunn (2010) by including a set of instruments as well as a standard set of county-level controls: median income, population density, crime rates (including violence and property crime). Instrumental variables used in this paper include the number of highway exits (Dunn, 2010), and the three-period lag of density of food environment components (Rashad, Grossman and Chou 2006). Highway exits are explicitly explained as

[15] An example from Dunn (2010) is that restaurants may be more likely to open in wealthier counties, which are also more likely to have grocery stores, clean parks and beaches, farmers' markets and low crime rates. Restaurants may concentrate in densely populated counties where individuals are more likely to walk to work or use public transportation. Alternatively, densely populated areas may inhibit exercise opportunities, such as bicycling or running. Counties with large distances between residential and commercial areas will tend to attract restaurants along commuting routes, and decrease the amount of time available for preparing meals at home and exercising. Another example is from Sturm (2008), who finds that convenience stores are located closer to the schools with more Hispanic and Black students.

valid instruments for fast food restaurants. Given that convenience stores are frequently combined with gas stations, which are generally located near highway exits, the number of highway exits is also a good instrument for convenience stores. In addition, food outlets usually expand based on market demand. The current availability of food outlets is likely to be correlated with consumers' demand in the current period or last several periods. To address this, three-year-lagged variables for food outlet availability are used as instruments because they are unlikely to correlate with the unobserved demand shocks (Rashad, Grossman and Chou 2006).

In addition, physical activity, risky behavior (smoking and drinking), and retirement are also potentially endogenous. For example, people who care more about their weight and health are more likely have higher level of physical activity. People who care less about their health may smoke and drink, resulting in different weight outcomes compared to non-smokers and non-drinkers. The endogeneity of these variables is addressed by using instrumental variables, including age, gender, income, and education, number of highway exits, population density, beer tax, cigarette tax, and wage rates. Limited maximum likelihood estimation is applied to estimate the model.

The estimated parameters (and associated statistics) of the full sample of New England counties (i.e., metropolitan counties and non-metropolitan counties), based on the U.S. Department of Agriculture (2013b) Rural-Urban Continuum

Codes shown in Table 2, are reported in Table 3. Metropolitan counties include three types of counties (codes 1, 2, 3) and non-metropolitan counties include six (codes 4, 5, 6, 7, 8, 9). In Table 3, nearly all parameters for the production frontier are statistically significant and show the expected signs. The estimated parameters show that age and number of children are positively associated with BMI. The impact of education level and income level is not linear. A higher level of education is associated with a higher BMI, while higher income level is negatively linked with BMI. Females, whites and Asians have relatively lower weights compared with Blacks and Hispanics. Married people are found to have higher BMIs. Behaviors like physical activity and drinking are negatively associated with high weight outcomes. Being retired is likely to increase weight.

In addition, the availability of fruit and vegetable restaurants and full-service restaurants, based on the full sample, is negatively associated with weight gain, while supercenters and limited-service restaurant are positively linked to weight outcomes. People in the counties with high median income or higher population density are found to have a lower likelihood of gaining weight.

The estimated parameters for metropolitan counties and non-metropolitan counties in Table 3 provide a different picture. Full-service restaurants are negatively associated with weight outcome for both metropolitan counties and non-metropolitan counties. In metropolitan counties, limited-service restaurants positively affect weight outcome.

To gain further insights, the model is estimated using six segmented samples. The first three are, respectively, “counties in metro areas of 1 million population or more,” “counties in metro areas of 250,000 to 1 million population,” “counties in metro areas of population less than 250,000.” The other three segments are “non-metro counties, urban population more than 2500 and adjacent to a metro area,” “non-metro counties, urban population more than 2500 and not adjacent to a metro area,” and “completely rural or urban population less than 2,500.” The parameter estimates and associated statistics are presented in Table 4 and Table 5.

Table 4 reports the results of three segments in metro counties. In the metro counties with populations greater than 1 million, fruit and vegetable stores and full-service restaurants contribute to BMI negatively, while supercenters and limited-service restaurants are positively associated with BMI. However, in the counties with populations between 250,000 and 1 million, supermarkets affect weight outcomes negatively. In the third segment of metropolitan counties (populations less than 250,000), no significant impacts are found. More interestingly, estimates for socio-economic factors indicate that significant effect by crime rate is only present in the counties with populations greater than 1 million. In those counties with higher crime rates, people are likely to have higher weight gain, a possible reason being that a high crime rate might discourage outdoor activity.

Table 5 reports the estimates results for another three segments in non-metro counties. Food environment only significantly affects BMI production inefficiency in counties adjacent to metro areas with populations of more than 2500. The empirical results show that supermarkets and full-service restaurants are negatively associated with weight outcomes, while limited-service restaurants are positively associated with weight outcomes. No significant estimates are found in counties that are not adjacent to a metro area with a population more than 2,500 or in counties that are completely rural. Another finding is that the crime rate is only significantly associated with BMI production in counties adjacent to metro areas.

With the estimate results, Farrell's (1957) technical efficiency index is calculated for each individual by county and presented in Table 6. (Due to missing data, six counties were dropped.) Suffolk County, in Massachusetts, ranks first and Somerset County, in Maine, last. Figure 2 is a map of the BMI production efficiency index from 2001-2010 using ArcMap 10.2, which is categorized into four levels illustrated by different colors. The low efficiency areas are clustered in northern New England (Maine) and high efficiency areas are clustered in southern New England (i.e., Connecticut).

2.5 Conclusions

This paper estimates the "efficiency" of weight production using a stochastic frontier model with individual and county-level data that includes nearly 200,000 observations in New England between 2001 and 2010. A major contribution of this paper is extending the framework of a health production function to a stochastic production model, which provides a useful approach for researchers and policy makers to evaluate the effects of changes in food environments on health outcomes, such as weight. Another contribution is the inclusion of all food environment components into a single analytical framework. Moreover, the paper contributes to the literature by investigating the effect of food environment within different contexts (i.e., metro counties v.s. non-metro counties), which provide policy makers with more accurate insights.

Empirical results confirm that the effects of food environment factors on BMI vary with a county's characteristics. For instance, both full-service and limited-service restaurants have significant effects on weight outcomes in counties with populations greater than 1 million, while convenience stores only significantly affect weight outcomes in counties with populations between 250,000 and 1 million. Supermarket and grocery stores exert negative impacts on weight outcomes in metro counties with population less than 1 million and non-metropolitan counties that are adjacent to a metropolitan area. These findings extend the existing literature, such as Anderson and Matsa (2009), Dunn (2010) and Chen et al. (2010).

As the estimation results suggest that the effects of food environment factors are concentrated in specific geographic contexts, any policy interventions intended to modify any food environment should take the location of counties into consideration. For example, restrictions on the fast food (e.g. hefty taxes) might be implemented in metro areas with populations greater than 1 million and non-metro counties adjacent to a metro area.

Another contribution of this paper is the inclusion of socio-economic factors in the investigation. For example, this paper finds that crime rate positively affects weight outcomes in metropolitan counties and rural counties adjacent to metropolitan areas, indicating that providing a safe living community is, potentially, and another way to curb prevalence of obesity.

All of these findings can help policy makers better understand the impact of changes in food environments on obesity and, as a result, to develop public policies to promote commercial development that is consistent with a healthier population. However, it is clear that there are many questions that our analysis does not answer. Further work would be fruitful in the following ways. First, one can investigate the relationship between food environment and weight outcomes with high-quality data sets that contain detailed information, such as locations of consumers as well as food outlets. Another direction could be an application of natural experiments, which can better address the endogeneity problem.

Chapter 3

Do Milk and Energy Prices Move Together?

3.1 Introduction

In the last decade, U.S. food and energy prices have experienced a dramatic increase, resulting in a dual food and energy price inflation that has had a significant negative impact on U.S. consumers. The previous literature sheds light mainly on the relation between oil prices and agricultural commodity and food prices. Generally speaking, the causal link between oil and food prices is explained by two mechanisms (Reboredo, 2012). First, oil affects production costs directly, given that agriculture is an energy-intensive sector. For example, Hanson, Robinson and Schluter (1993) find that an increase in oil prices caused a rise in input costs and a corresponding rise in agricultural commodity prices. The strength of this effect depends on several factors, such as the relative importance of oil in the production cost structure and the market power of agriculture to pass costs on to prices. Second, on the demand side, the increased price of oil has significantly raised demand for corn- and soybean-based biofuels. Chen, Kuo and Chen (2010) show that higher crude oil prices have induced a higher derived demand for corn and soybean and greater competition for the planted areas of other grains, resulting in changes in grain prices for corn, soybeans and wheat.

Previous studies have also found evidence of oil and agricultural commodity price causality. Hameed and Arshad (2008) report evidence of the influence of oil on food prices based on cointegration analysis. Nazlioglu (2011) provides evidence of a non-linear relation between oil and agricultural prices. Furthermore, partial and general equilibrium models have also been widely used to access the sensitivity of agricultural commodity prices to oil price shocks (e.g., Ignaciuk and Dellink, 2006).

However, some empirical studies have found no evidence regarding an oil-food price nexus. For example, Zhang et al. (2010) find agricultural commodity prices to be neutral to the effects of oil price changes over the long run. Gilbert (2010) explains the recent upward trend in agricultural prices by distinguishing between common and market-specific factors, reporting evidence of the neutrality of market factors like oil price and biofuel demand.

In a word, to the best of my knowledge, the previous studies have linked agricultural commodities and price indexes to oil price rather than focusing on specific retail products. More specifically, there are no previous studies directly linking milk and energy prices, although the relationship between milk and energy prices is so important to daily life.

Milk and milk prices provide a good case study for examining the relation between energy and food price inflation. First, as a staple food, milk is more nutritious (proteins, minerals and vitamins) and contains fewer calories than other beverages, particularly carbonated soft drinks and fruit juices. More importantly, given the prevalence of obesity and over-consumption of soda, milk is considered a good substitute for soda (Runge, Johnson and Runge, 2011). Milk prices are closely connected with consumers' welfare and social well-being, particularly children's, highlighting the importance of understanding the relationship between energy and milk prices. Third, energy (e.g., diesel) price plays an important role in milk production as well as transportation (Brush, Masanet and Worrell, 2011).

This paper estimates the demand for fluid milk in Boston with a random coefficient logit model, which allows a more flexible curvature of the demand curve. This property provides flexible pass-through rates that are not driven solely by the functional form assumption. Empirical results indicate consumers prefer milk products with lower prices, lower fat content and smaller sizes. In addition, consumers prefer to buy private labels compared with other brands. This research also finds that private labels have lower elasticities as well as higher market power. Finally, energy prices (e.g., diesel and electricity) significantly impact the cost of milk products. The pass-through rates are around 0.6227. More interestingly, most of the private labels are found with the lowest energy (diesel) pass-through rate, which is consistent with the relatively stable price of private labels, indicating that private labels are less vulnerable to energy price shocks.

3.2 Empirical Strategy

Cost pass-through rates measure the proportion of a change in input costs that is transmitted to price (Kim and Cotterill, 2008). There are two ways in which to model price pass-through: (1) a reduced form or single equation model; (2) a structural model involving demand and supply. A reduced-form analysis is simple but disadvantageous for inferring the degree of market competitiveness without knowing the benchmark pass-through rate (Kim and Cotterill, 2008). In this study, a structural model is applied with consideration of firms' competitive interaction. This study uses a random coefficient logit model to capture consumer choices in the context of product and consumer heterogeneity. The supply side (i.e., margins or marginal costs) is derived in a post-demand estimation stage. The indirect utility of consumer i from purchasing milk brand j in market m is:

$$u_{ijm} = \delta_{jm} + \mu_{ijm} + \epsilon_{ijm}, \qquad 3.2.1$$

where the indirect utility u_{ijm} can be decomposed into three parts: a mean utility term δ_{jm}, which is common to all consumers; a brand-specific and consumer-specific deviation from that mean μ_{ijm}; and idiosyncratic tastes ϵ_{ijm}, where ϵ_{ijm} is a mean zero stochastic term distributed independently and identically as a type I extreme value distribution. The mean utility $\delta_{jm} = X_j' \beta + \xi_{jm}$ includes a vector X_j of key product characteristics of relevance to consumers; ξ_{jm} is unobserved product characteristics. The utility deviations are $\mu_{ijm} = X_j' \Sigma V_i$, where Σ is a scaling matrix, and random part V_i are assumed to have a standard multivariate normal distribution. Then the probability that consumer i purchases a unit of brand j in market m is,

$$s_{ijm} = \frac{exp(\delta_{jm}+\mu_{ijm})}{1+\sum_{r=1}^{J} exp(\delta_{rm}+\mu_{irm})}. \qquad 3.2.2$$

The market share of the j th brand corresponds to the probability that the jth brand is chosen in market m, given by

$$s_{jm}(p,x,\theta) = \int I\{(\nu_i,\epsilon_{ijm}): U_{ijm} \geq U_{ikm}\ \forall k = 0,\dots,J\} dG(\nu)dF(\epsilon), \qquad 3.2.3$$

where θ is a vector of consumer taste parameters; $k=0$ denotes the outside good; and $G(v)$ and $F(\epsilon)$ are cumulative density functions for the indicated variables, assumed to be independent of each other.

The price elasticities of brand j in market m can be expressed as below:

$$\eta_{jm} = \frac{\partial s_{jm}}{\partial p_{km}} \cdot \frac{p_{km}}{s_{jm}} = \begin{cases} \dfrac{p_{jm}}{s_{jm} \int \alpha_i s_{ijm}(1-s_{ijm}) dG(\nu)}, & for\ j = k, \\ \dfrac{-p_{km}}{s_{jm} \int \alpha_i s_{ijm} s_{ikm} d(\nu)}, & otherwise, \end{cases} \qquad 3.2.4$$

where α_i denotes price coefficient of individual i.

Since the pass-through rate depends on the demand and supply elasticity, a suitable model of a firm's behavior is of great importance for the pass-through estimate. Berry, Levinsohn and Pakes (1995) assume the firm behaves under Bertrand-Nash pricing strategies. Kim and Cotterill (2006) estimate cost pass-through rates under Bertrand-Nash pricing and collusive pricing. Nevo (2001) assume the existence of a pure-strategy Bertrand-Nash equilibrium in prices. This research presented here follows Berry, Leninsohn and Pakes (1995) and Nevo (2001) and assumes a Betrand-Nash equilibrium.

Assuming marginal costs are constant for each product but vary across markets, the firm f's profit in market m given by:

$$\pi_f^m = \sum_{j \in J_f} \left(p_{jm} - mc_{jm}\right) M s_{jm}(p) , \qquad 3.2.5$$

where mc_{jm} is the marginal cost of brand j in market m, J_f is the set of brands produced by firm f, M is market size, $s_{jm}(p)$ is the market share of brand j in market m. The first order condition is:

$$\frac{\partial \pi_f^m}{\partial p_{km}} = M \left[s_{jm}(p) + \sum_{j \in J_f} \left(p_{jm} - mc_{jm}\right) \frac{\partial s_{jm}}{\partial p_{km}} \right] = 0, \qquad 3.2.6$$

Rewriting F.O.C in vector notation, the conceptual pricing equation is:

$$p - mc = \left[\Theta^{own} * \left(-\frac{\partial s(p)}{\partial p} \right) \right]^{-1} s(p) \qquad 3.2.7$$

where

$$\Theta_{i,j}^{own} = \begin{cases} 1, \text{if } i, j \text{ are produced by same firm,} \\ 0, \text{otherwise,} \end{cases}$$

Following Chidmi, Lopez and Cotterill (2005) as well as Richards et al. (2012), the marginal cost is assumed as a functional of raw milk price P_f, diesel price P_d, electricity price P_e, package size S, and fat content F, and month dummies, denoted as D. The marginal cost function then is:

$$mc = f\left(P_f, P_d, P_e, S, F, D \right). \qquad 3.2.8$$

The most common forms for marginal cost function in the previous literature are the log-linear form of Berry et al. (1995) and Sudhir (2001), which gives the estimating equation:

$$Logmc = \alpha_0 + \alpha_1 logP_f + \alpha_2 logP_d + \alpha_3 logP_e + \alpha_4 logS + \alpha_5 logF + \alpha_6 logD + \varepsilon_1 \qquad 3.2.9$$

where $\varepsilon_1 \sim N(0, \sigma_{\varepsilon_1}^2)$ are the unobservable factors such as marketing costs.

On the other side, the raw milk price is also a function of energy price, which is model as:

$$logP_f = \beta_0 + \beta_1 logP_{feed} + \beta_2 logP_d + \beta_3 logP_e + \beta_4 logD + \varepsilon_2 \qquad 3.2.10$$

where ε_2 are the unobservable factors that affect the raw milk price. $\varepsilon_2 \sim N(0, \sigma_{\varepsilon_2}^2)$

Energy shocks are transmitted to the milk price in the following two paths: (1) via diesel price directly (i.e., $\frac{\partial f}{\partial P_d}$); (2) via raw milk price (i.e., $\frac{\partial f}{\partial P_f}\frac{\partial P_f}{\partial P_d}$);

Given that this essay focuses on the pass-through rate of diesel price, a new model specification is obtained by substituting equation 3.2.10 into equation 3.2.9:

$$Logmc = (\alpha_1\beta_0 + \alpha_0) + \alpha_1\beta_1 logP_{feed} + (\alpha_1\beta_2 + \alpha_2)logP_d + (\alpha_1\beta_3 + \alpha_3)logP_e + \alpha_4 logS + \alpha_5 logF + (\alpha_1\beta_4 + \alpha_6)logD + (\varepsilon_1 + \alpha_1\varepsilon_2), \quad 3.2.11$$

where ε_1 and ε_2 are random shocks from different aspects, which can be assumed independent with each other, so $\varepsilon_1 + \alpha_1\varepsilon_2 \sim N(0, \sigma_{\varepsilon_1}^2 + a_1^2\sigma_{\varepsilon_2}^2)$.

Denote $\lambda_0 = \alpha_1\beta_0 + \alpha_0$; $\lambda_1 = \alpha_1\beta_1$; $\lambda_2 = \alpha_1\beta_2 + \alpha_2$; $\lambda_3 = \alpha_1\beta_3 + \alpha_3$; $\lambda_4 = \alpha_1\beta_4 + \alpha_6$; $\varepsilon = \varepsilon_1 + \alpha_1\varepsilon_2$, the model is:

$$Logmc = \lambda_0 + \lambda_1 logP_{feed} + \lambda_2 logP_d + \lambda_3 logP_e + \alpha_4 logS + \alpha_5 logF + \lambda_4 logD + \varepsilon \quad 3.2.12$$

After getting parameter estimates for equation 3.2.12, assume there is a positive diesel price shock from $\overline{P_d}$ to $\widehat{P_d}$. Corresponding to the energy price shock, the market price will converge to a new equilibrium, $\hat{P}$. The diesel price pass-through rate (Γ) is then defined as the ratio of the price change to the change in diesel price:

$$\Gamma = \frac{\Delta p}{\Delta P_d} \times 100, \quad 3.2.13$$

where Δp is the difference between the new equilibrium price and old price and $\Delta P_d = \widehat{P_d} - \overline{P_d}$.

3.3 Data

The milk sales data come from the Information Resources Incorporated (IRI) database provided by the Zwick Center for Food and Resource Policy at the University of Connecticut. The milk data set contains brand-level information in the greater Boston area for four-week periods from January 2009 to December 2011. Product characteristics include brand name (Garelick Farms, Garelick Farms over the Moon, Hood, Hood Lactaid, Hood Simply Smart, Private Label, Smart Balance, Stoneyfield Farm), fat content (0, 1%, 2% and 3.25%), lactose content (free or not) and package size. Following Lopez and Lopez (2009), all milk types with less than 0.5% market share are dropped, which generates 56 products described by these four characteristics, which are shown in Table 1.

Retail prices are computed by dividing the dollar sales by volume sold. Market shares for each product are computed with respect to the potential market for milk, which was calculated by multiplying the total population of the Boston area by the average U.S. per capita milk consumption (USDA, 2012). The outside good is defined as the part of the potential market that is not considered in the sample, i.e., the total amount of fluid milk sold in the Boston area that is either not part of the 56 milk products in the sample or that is sold in other retail outlets. As a result, the volume of milk included in the data set used in this study represents approximately 65% of the potential market. Each time period was treated as a market consisting of 56 products and 200 consumers, which generated 2016 markets (56 products*36 month=2016) and 403200 (2016*200) consumer observations.

The diesel prices are from the Mid-Atlantic Information Office of the Bureau of Labor Statistics (BLS, 2013), which are average monthly retail prices from 2009 to 2011. Electricity prices are from the U.S Energy Information Administration (EIA, 2009-2011).

3.4 Estimation and Results

Instrumental variables are used to address the endogeneity of price. Assume that demand shock ϵ is independent of a set of exogenous instruments, ω (i.e., $E[\epsilon|\omega] = 0$). The instrumental variables used include cost shifters of milk (diesel price, electricity rate, wage rate, interest rate) (Berry, Levinsohn and Pakes, 1999, Nevo, 2001), products' average price in other markets (Hausman and Taylor, 1981), as well as brand dummies, month dummies and non-price product characteristic variables. Optimal instruments are also used to help to identify random coefficients and increase efficiency. Chamberlain (1987) shows that the efficient instruments are the expected values of the derivatives of the conditional moment condition with respect to the parameter, under conditional moment restrictions. Berry, Levinsohn and Pakes (1999) propose to use approximations to the optimal instruments for the BLP model. Reynaert and Verbovern (2012) demonstrate that both the performance of the approximation and the exact implementation of optimal instruments can overcome several estimation problems of the BLP model and increase substantially the estimation efficiency and stability. This research, following Chen (2013), denotes the vector of parameter as $\theta = [\beta, \sigma]$. The optimal instruments are given by Chamberlain (1987), Berry, Levinsohn and Pakes (1999) and Raynaert and Verboven (2012):

$$\mathbb{Z} = E\left[\frac{\partial \xi(\theta)}{\partial \theta}\middle|\bar{X}, \omega\right] = E[\frac{\partial \delta(s,\sigma)}{\partial \theta}|\bar{X}, \omega], \qquad 3.4.1$$

where δ is the mean utility and s is the market share.

By replacing the expected values of the derivatives in equation 3.4.1 with the appropriate derivatives evaluated at the expected value of the unobservables, the approximated optimal instruments are constructed using the following procedure:

(a) Obtain an initial estimate $\widehat{\theta_0} = [\beta_0, \sigma_0]$ by using exogenous instrumental variables ω

(b) Compute the predicted price $\hat{p}$ from a first–stage OLS regression, which is also the optimal instrument for price coefficient

(c) Compute the predicted mean utility $\widehat{\delta_0} = [\bar{X}, \hat{p}]'\widehat{\beta_0}$

(d) Compute the predicted market share. $\widehat{s_0} = s(\widehat{\delta_0}, \widehat{\sigma_0})$

(e) Compute the optimal instruments with respect to σ: $\frac{\partial \delta(\widehat{s_0}, \widehat{\sigma_0})}{\partial \widehat{\sigma_0}}$

The demand model specified can be estimated with the complete set of instrumental variables, including cost shifters, Hausman-type instruments and Chamberlain-type optimal instruments, using a non-linear Generalized Methods of Moments (GMM) estimator. This research follows Berry, Levinsohn and Pakes (1995) and Dubé et al. (2012), applying mathematical program with equilibrium constraints (MPEC) approach to estimate parameters of the demand model.

The predicted market shares are restricted to match the observed shares, where δ can be solved from:

$$s(\delta_t, \sigma) - s = 0 \qquad 3.4.2$$

Let IV be the full set of instrumental variables. The moment conditions are given by:

$$g(\delta) = E[IV'\xi] = E[IV'(\delta - X'\beta)] = 0 \qquad 3.4.3$$

Let Λ be the GMM weight matrix and θ be the vector of parameters. The estimated parameters can be solved from the following constrained minimization problem:

$$min\, g' \Lambda g$$

$$\text{s.t.} \quad s(\delta_t, \sigma) - s = 0$$

$$\mathrm{E}[IV'(\delta - X'\beta)] = 0 \qquad 3.4.4$$

The estimated demand parameters are used to calculate product-specific price elasticities and the retailer price-cost margins. Based on the estimates, the pass-through rate is calculated by simulation. All the results are presented in the following section.

Table 3.2 illustrates the estimation results [16]. Overall, the results seem plausible in terms of signs and expected coefficients. On average, consumers have a negative and strong valuation of price, fat content and size. Comparing with other brands, consumers prefer private labels, which is consistent with the finding of Lopez and Lopez (2009). On the other side, the estimated parameter for lactose-free is positive but insignificant. Table 3.2 also shows consumers' significant heterogeneous preference for milk product characteristics such as price, fat contents and private labels, which confirms the variety of consumers' preferences in the Boston fluid milk market.

Table 3.3 illustrates that all the own-price elasticities of demand are negative and all cross-price elasticities are positive for the milk products. For the private labels, the own-price elasticities are comparatively lower than those of other brands, which indicate that private labels are exerting more market power. Totally speaking, the values of the estimated own-price elasticities range from -9.521 for non-fat, one gallon private label milk, to -12.277 for 1% fat, one gallon Hood milk. These estimates of elasticities are within the range of conclusions given in previous studies focusing on fluid milk. For instance, Cotterill and Dhar (2003) provide

[16] A preliminary analysis is given in the Appendix 1

own-price elasticities estimates as high as -35 for Hood milk and -3.62 for private label milk, while Lopez and Lopez (2009) find that the elasticities for milk in Boston range from -1.98 for 1% low fat private label milk to -8.52 for 1% lactose free Morningstar milk. Kinoshita, Suzuki, and Kaiser (2002), with scanner brand-level data in Japan, find price elasticities in the range of -6.67 to -9.19. It is not surprising that the elasticities estimates in this research are relatively higher compared to those brand-level studies. A possible explanation is that this paper focuses on product level, which is smaller and defined by specific product characteristics, as opposed to brand level. In this research consumers have more substitutes to switch to, resulting higher price elasticities.

Table 3.4 shows that private label has the highest Lerner Index, i.e., the highest percent markup. This result is consistent with the finding of Lopez and Lopez (2009). One explanation is that, although the price of private label is relatively lower than other products, the marginal cost is also low so that the markup can be even higher than on other products.

Table 3.5 reports the estimation results of marginal cost function in three model specifications. Comparing with model 1, model2 includes company fixed effects which capture the effects of unobservable shocks, such as advertising and other marketing strategies. Model 3 includes both company dummies as well as month and year fixed effects, which control the unobservable factors varying with time such as temperature and energy policy (e.g., biological ethanol). Based on the BIC and R-square, model 2 outperforms model 1 as well as model 3. The results show that a 1% diesel price increase will lead to a 0.42% increase of marginal cost, while a 1% electricity price increase leads to a 3.24% increase of marginal cost. The estimation results also show that a 1% package size increase will lead to a 0.51% decrease of marginal cost. One possible reason could be the decreasing returns to scale. Finally, Table 3.5 shows that products with higher fat content have lower marginal cost, which is plausible because skimming the fat needs more inputs (e.g., energy consumption, labor inputs).

Table 3.6 illustrates the estimated energy (diesel) pass-through rate for 56 products. The pass-through rate ranges from 0.5539 to 0.6966, with a mean of 0.6227, which indicates that, on average, a dollar increase in diesel price will lead to 0.6227 of a dollar increase of milk price. In addition, the results show that the pass-through rates of private label products, generally speaking, are lower than those of other brands. These findings indicate that the private labels are less vulnerable to energy shock compared with other brands. One possible reason can be the higher price-cost markups of private labels. When energy shocks increase the cost, it is still profitable for private labels by increasing price by a smaller amount comparing with other brands. Also, consumers might switch from other products the private labels because of their slowly increasing price.

3.5 Conclusions

This essay investigates the demand for a differentiated product market (Boston fluid milk) and implements pass-through simulations. The demand is estimated with a framework of random coefficient logit model, which allows a more flexible curvature of demand curve. This property provides flexible pass-through rates that are not driven solely by the functional form assumption.

Empirical results indicate that fluid milk products with lower price, lower fat content and smaller sizes are more popular. Empirical results also show that the private labels have lower price elasticities as well as the highest degrees of market power. This finding lends support to previous studies that have similarly found that more basic products (in this case, private label milks) benefit from greater price-cost margins (Lopez and Lopez, 2009). In addition, this research also finds that energy prices (e.g., diesel and electricity) significantly impact the prices of milk products. The pass-through rates are around 0.6227. More interestingly, most private labels are found with the lowest energy (diesel) pass-through rates, which is consistent with the relatively stable price of private label products. This finding also implies that compared to other products, private labels are less vulnerable to energy price shocks.

Future study can be fruitful in the following routes. One is to investigate different kinds of energy shocks comprehensively. Another one is to put energy policy such biological ethanol under consideration, which could make the results more solid. As for methodology, a difference in differences approach can be another powerful tool to provide insights in this research.

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Appendix 1: Preliminary Analysis: Causality Test

Table A.1 gives Augmented Dickey-Fuller test (ADF-test) statistics for milk and diesel prices. The test statistics reject the null hypothesis that milk and diesel price (in first order difference) are non-stationary, indicating that both are stationary. Table A.2 shows the Johansen Test results. Based on the Trace Statistics, the hypothesis that maximum rank ≤ 0 is rejected, while Rank$\leq$ 1is not rejected, which implies that milk price and diesel price are cointegrated. Table A.3 gives the results of Granger causality test for Milk and Diesel price. The results indicate that the diesel is Granger-cause of milk.

Table A.1: ADF test for Stationary of Milk and Diesel Price (First Order Difference)

	Test Statistics	1% Critical Value	MacKinnon p-value
Milk	-4.265	-3.478	0.001
Diesel	-4.755	-3.478	0

Table A.2: Johansen Test for Cointegration: Milk and Diesel Price

Maximum Rank	Eigenvalue	Trace Statistics	5% Critical Value
0	---	34.978	15.41
1	0.144	2.518*	3.76
2	0.012		

Table A.3: Granger Causality Test for Milk and Diesel Price

Ho	**F statistics (P value)**	**Chi-Square(P value)**	**Reject or Not**
Diesel does not Granger-cause milk	3.31(0.039)	6.78(0.034)	Reject
milk does not Granger-cause diesel	**0.83(0.478)**	**2.58(0.461)**	**Not Reject**

Note: The choice of lags based on the minimum value of AIC and BIC.

Figure A.1 Price of diesel and milk: 1998-2014

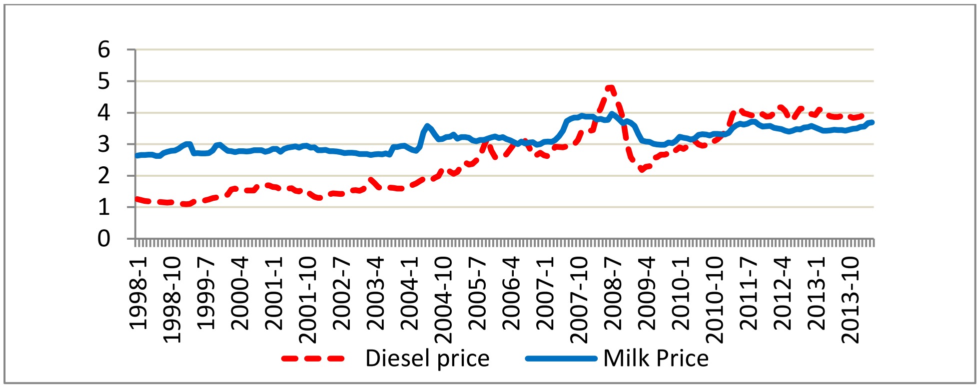

Figure A.2 First order difference of diesel price: 1998-2014

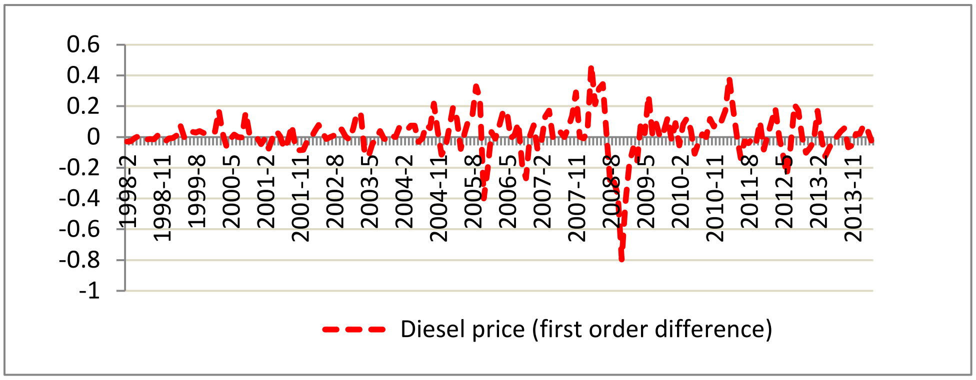

Figure A.3 First order difference of milk price: 1998-2014

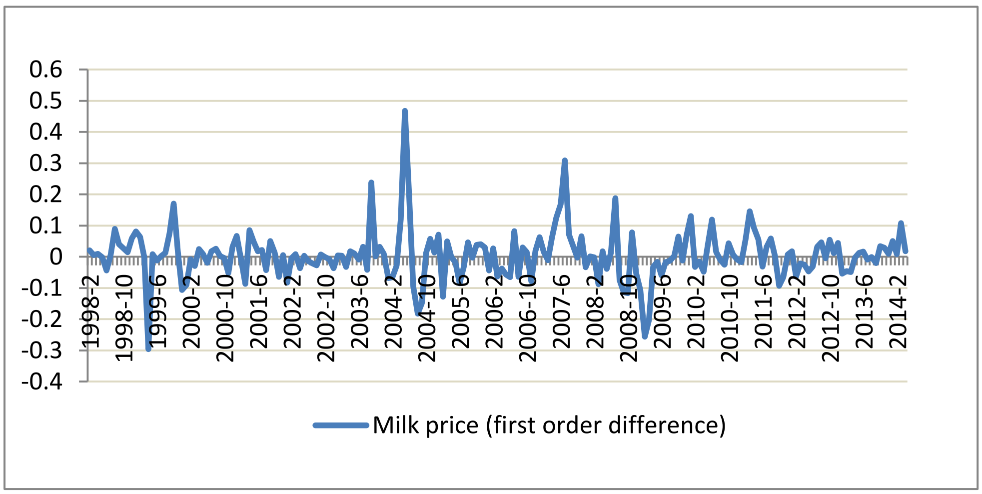

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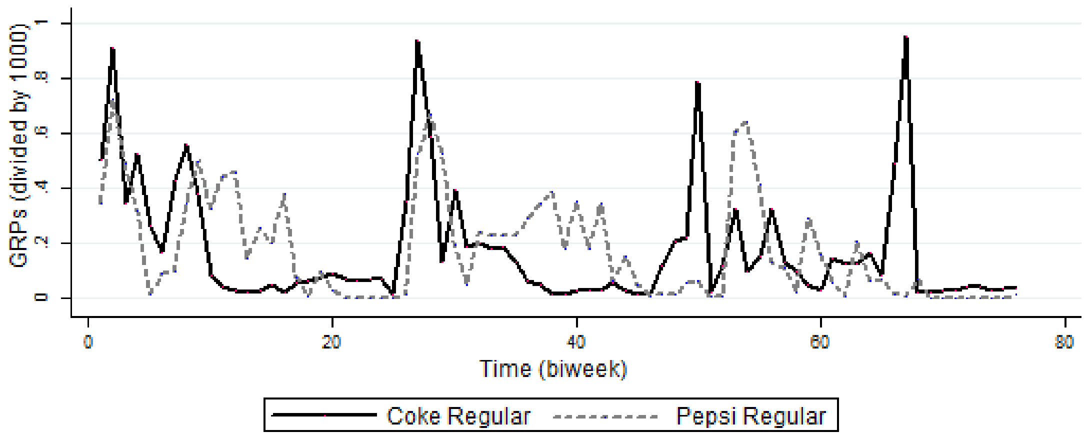
Figure 1.1 GRPs for Coke Regular and Pepsi Regular in Boston: 2006-2008



Source: Constructed by authors based on television advertising dataset from the Nielsen Company

Figure 2.1 Stochastic Frontier for BMI Production

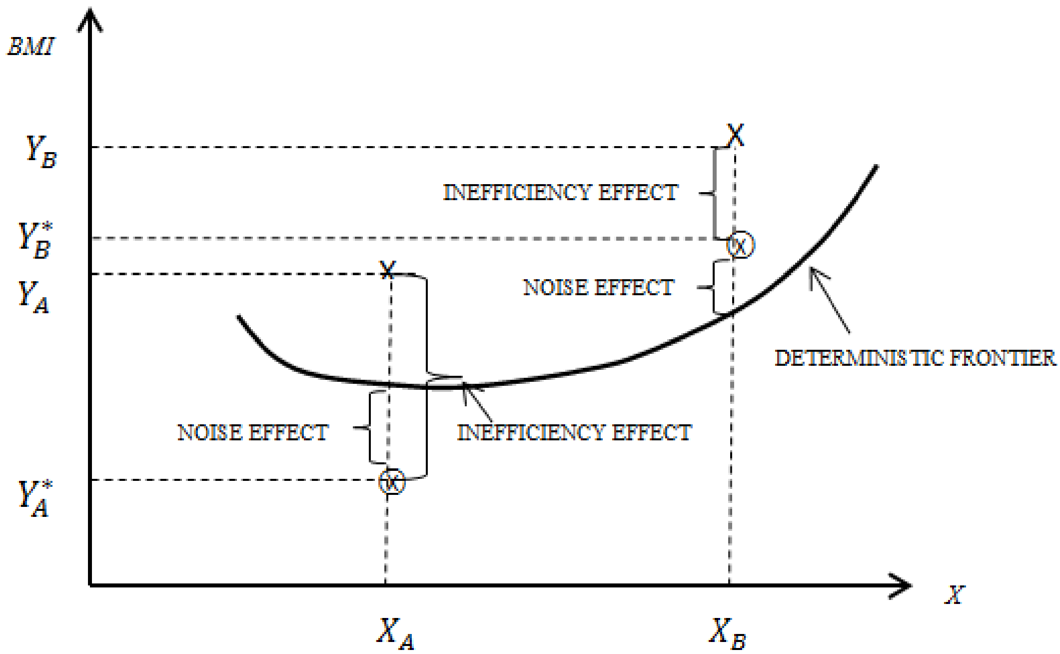


Figure 2.2: BMI production efficiency indexes in New England counties

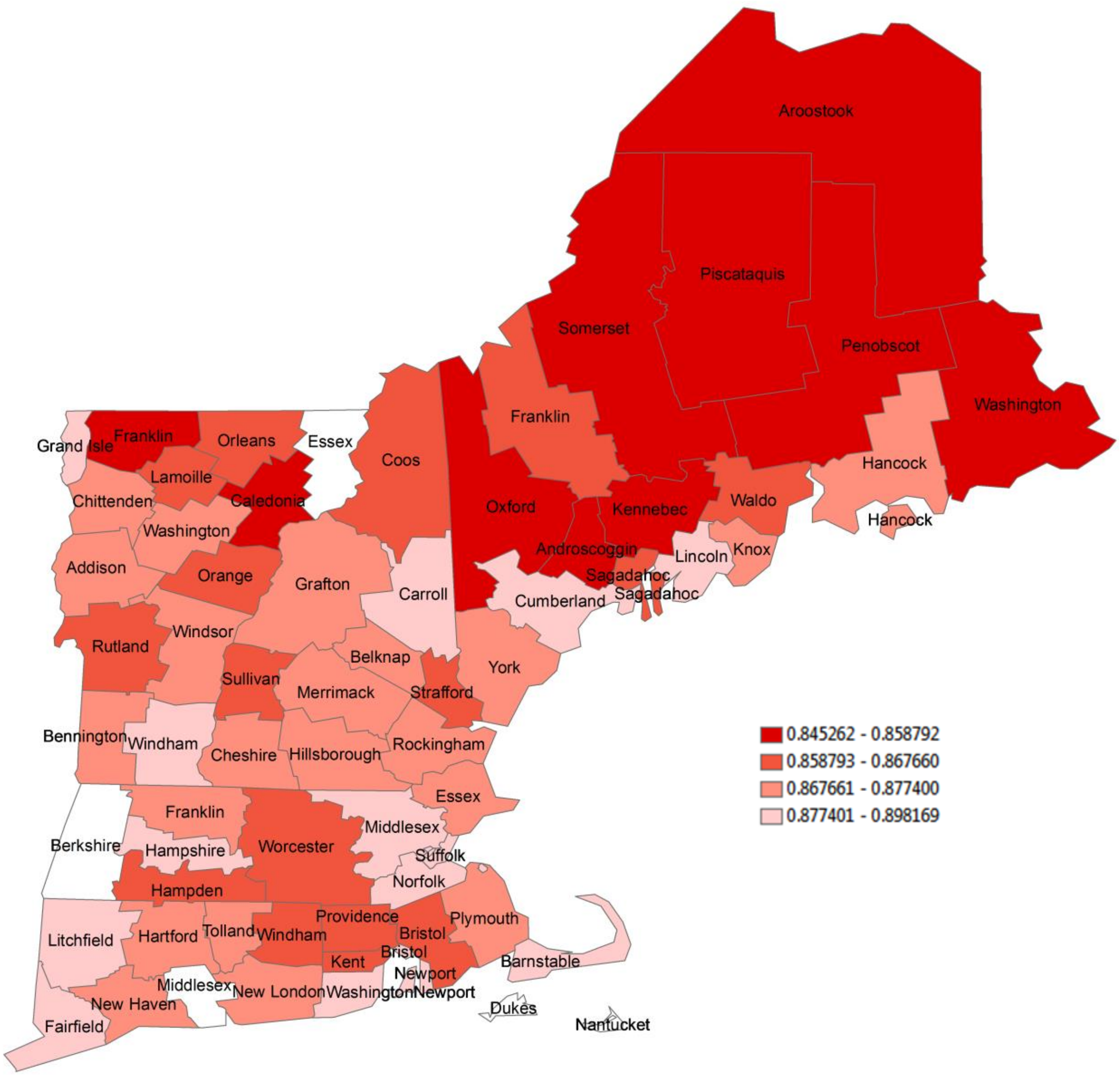


Table 1.1 Summary of Carbonated Soft Drink Brand Characteristics and Market Shares

Company/Brand	Price $/12 oz.	Market Share (%)	Weekly GRP	Calories per 12 oz.	Sugar g/12oz	Sodium mg/12oz	Caffeine mg/12oz
Coca-Cola							
Coke Reg.	0.36	5.17	194.3	140	39	50	35
Coke Diet	0.37	4.54	101.4	0	0	40	47
Sprite Reg.	0.41	1.14	109.7	144	38	70	0
Coke Zero Diet	0.43	0.74	127.5	0	0	40	35
Pepsi							
Pepsi Reg.	0.32	4.56	180.0	150	41	30	38
Pepsi Diet	0.34	3.11	98.3	0	0	35	35
Mountain Dew Reg.	0.37	1.54	131.3	170	46	65	54
Sierra Mist Reg.	0.35	0.59	47.0	150	39	38	0
Mountain Dew Diet	0.34	0.55	82.8	0	0	50	54
Dr. Pepper							
Dr Pepper Reg.	0.38	1.49	192.9	150	40	55	42
Dr Pepper Diet	0.38	1.06	70.7	0	0	55	42
Sunkist Reg.	0.37	0.63	18.3	190	50	70	40
7 Up Reg.	0.32	0.58	169.7	140	38	40	0
7 Up Diet	0.31	0.46	8.3	0	0	65	0

Note. Results are averages over 76 biweekly periods in nine designated market areas during 2006-2008.

Source: The Nielsen Company

Table 1.2 Carbonated Soft Drink Demand Results for Alternative Advertising Models

Variables	Model 1 No Adv. Spillovers	Model 2 Linear Adv.	Model 3 CES Adv.
Price	-1.948***	-1.939*	-2.683***
	(0.556)	(0.679)	(0.596)
Sugar	0.055***	0.069***	-0.006
	(0.018)	(0.018)	(0.016)
Sodium	-0.931***	-0.924***	-0.598***
	(0.047)	(0.050)	(0.047)
Caffeine	0.345***	0.339***	0.206***
	(0.025)	(0.026)	(0.023)
Brand Advertising	0.161***	0.192***	0.240***
	(0.024)	(0.024)	(0.034)
Company Advertising	---	0.110***	0.745***
		(0.012)	(0.034)
Competitors' Advertising	---	-0.049***	-0.048***
		(0.009)	(0.008)
Within-Group Market Share	0.872***	0.882***	0.905***
	(0.009)	(0.009)	(0.009)
Substitution Parameter ρ	---	---	0.052***
			(0.009)
Returns to Scale Parameter k	---	---	0.194***
			(0.019)
Elasticity of Substitution γ	---	---	1.055***
			(0.010)
Season Fixed Effects DMA	YES	YES	YES
DMA Fixed Effects	YES	YES	YES
First Stage F Stat.			
Price (p-value)	17.224 (0.000)	12.865(0.000)	12.865(0.000)
Within-Group Mk. Sh. (p-value)	1578.750 (0.000)	1568.000(0.000)	1568.000(0.000)
Company Advertising	31428.900(0.000)	30764.600(0.000)	30764.600(0.000)
Sargan Stat. (p-value)	0.461 (0.794)	0.497(0.780)	3.528(0.171)
Durbin Score (p-value)	82.724 (0.000)	79.817(0.000)	18.794(0.000)
Out of Sample MSE	0.414	0.452	0.380
RMSPE	0.1623	0.1610	0.1468
Observations	8820	8820	8820

Note. Robust standard errors are in parentheses. Elasticity of substitution is computed based on substitution parameter ρ. * indicates a 10% significance level. *** indicates a 1% significance level.

Source: Constructed by authors

Table 1.3 Sample of Price Elasticities of Demand under Alternative Model Specifications

Model 1: No Advertising Spillovers

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr Pepper Regular	Dr Pepper Diet
Coke Regular	**-1.465**	0.853	0.012	0.009	0.005	0.003
Coke Diet	0.946	**-1.629**	0.012	0.009	0.005	0.003
Pepsi Regular	0.016	0.014	**-1.325**	0.605	0.005	0.005
Pepsi Diet	0.016	0.014	0.832	**-1.695**	0.003	0.003
Dr Pepper Regular	0.016	0.014	0.012	0.009	**-1.803**	0.527
Dr Pepper Diet	0.016	0.014	0.012	0.009	0.713	**-1.835**

Model 2: Linear Advertising Spillovers

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr Pepper Regular	Dr Pepper Diet
Coke Regular	**-1.572**	0.931	0.012	0.009	0.005	0.003
Coke Diet	1.033	**-1.750**	0.012	0.009	0.005	0.003
Pepsi Regular	0.016	0.014	**-1.422**	0.660	0.005	0.003
Pepsi Diet	0.016	0.014	0.907	**-1.823**	0.005	0.003
Dr Pepper Regular	0.016	0.014	0.012	0.009	**-1.938**	0.575
Dr Pepper Diet	0.016	0.014	0.012	0.009	0.778	**-1.975**

Model 3: CES Advertising Spillovers

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr Pepper Regular	Dr Pepper Diet
Coke Regular	**-2.661**	1.636	0.017	0.012	0.006	0.004
Coke Diet	1.815	**-2.971**	0.017	0.012	0.006	0.004
Pepsi Regular	0.022	0.019	**-2.408**	1.161	0.006	0.004
Pepsi Diet	0.022	0.019	1.595	**-3.107**	0.006	0.004
Dr Pepper Regular	0.022	0.019	0.017	0.012	**-3.298**	1.013
Dr Pepper Diet	0.022	0.019	0.017	0.012	1.370	**-3.370**

Table 1.4 Sample of Advertising Elasticities under Alternative Model Specifications

Model 1: No Advertising Spillovers

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr Pepper Regular	Dr Pepper Diet
Coke Regular	**0.437**	-0.133	-0.004	-0.001	-0.002	-0.003
Coke Diet	-0.289	**0.241**	-0.004	-0.001	-0.002	-0.003
Pepsi Regular	-0.005	-0.002	**0.446**	-0.084	-0.002	-0.003
Pepsi Diet	-0.005	-0.002	-0.277	**0.227**	-0.002	-0.003
Dr Pepper Regular	-0.005	-0.002	-0.004	-0.001	**0.575**	-0.050
Dr Pepper Diet	-0.005	-0.002	-0.004	-0.001	-0.240	**0.168**

Model 2: Linear Advertising Spillovers

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr Pepper Regular	Dr Pepper Diet
Coke Regular	**0.562**	0.018	-0.146	-0.075	-0.189	-0.055
Coke Diet	0.327	**0.310**	-0.146	-0.075	-0.189	-0.055
Pepsi Regular	-0.143	-0.079	**0.573**	0.167	-0.189	-0.055
Pepsi Diet0.034	-0.143	-0.079	0.329	**0.292**	-0.189	-0.055
Dr Pepper Regular	-0.143	-0.079	-0.146	-0.075	**0.741**	0.124
Dr Pepper Diet	-0.143	-0.079	-0.146	-0.075	0.424	**0.217**

Model 3: CES Advertising Spillovers

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr Pepper Regular	Dr Pepper Diet
Coke Regular	**0.256**	0.174	-0.176	-0.090	-0.228	-0.067
Coke Diet	0.674	**0.258**	-0.176	-0.090	-0.228	-0.067
Pepsi Regular	-0.172	-0.095	**0.255**	0.221	-0.228	-0.067
Pepsi Diet	-0.172	-0.095	0.509	**0.245**	-0.228	-0.067
Dr Pepper Regular	-0.172	-0.095	-0.176	-0.009	**0.251**	0.294
Dr Pepper Diet	-0.172	-0.095	-0.176	-0.009	0.470	**0.239**

Table 1.5 Price-Cost Markups ($/12 oz.) and Lerner Indexes for the Top 14 Carbonated Soft Drink Brands

	No Spillovers		Linear Spillovers		CES Spillovers	
Brand	Markup	Lerner Index	Markup	Lerner Index	Markup	Lerner Index
Coke Reg.	0.111	0.321	0.103	0.300	0.061	0.177
	(0.014)	(0.084)	(0.014)	(0.078)	(0.008)	(0.047)
Coke Diet	0.109	0.353	0.102	0.330	0.060	0.195
	(0.016)	(0.088)	(0.015)	(0.082)	(0.009)	(0.050)
Sprite Reg.	0.102	0.284	0.095	0.265	0.056	0.156
	(0.012)	(0.065)	(0.012)	(0.061)	(0.007)	(0.036)
Coke Zero	0.091	0.283	0.084	0.263	0.049	0.154
	(0.010)	(0.079)	(0.009)	(0.073)	(0.006)	(0.044)
Pepsi Reg.	0.096	0.283	0.089	0.263	0.053	0.155
	(0.018)	(0.106)	(0.017)	(0.099)	(0.011)	(0.059)
Pepsi Diet	0.076	0.223	0.071	0.207	0.041	0.121
	(0.006)	(0.065)	(0.006)	(0.060)	(0.003)	(0.035)
Mountain Dew Reg.	0.072	0.196	0.067	0.181	0.039	0.106
	(0.003)	(0.050)	(0.003)	(0.046)	(0.002)	(0.027)
Sierra Mist Reg.	0.087	0.278	0.080	0.259	0.047	0.152
	(0.014)	(0.116)	(0.014)	(0.108)	(0.008)	(0.064)
Mountain Dew Diet	0.070	0.201	0.065	0.186	0.038	0.108
	(0.003)	(0.079)	(0.002)	(0.073)	(0.001)	(0.043)
Dr. Pepper Reg.	0.077	0.258	0.072	0.240	0.042	0.140
	(0.010)	(0.162)	(0.010)	(0.151)	(0.006)	(0.088)
Dr. Pepper Diet	0.069	0.236	0.064	0.218	0.038	0.127
	(0.003)	(0.123)	(0.003)	(0.114)	(0.002)	(0.066)
Sunkist Reg.	0.075	0.255	0.070	0.236	0.041	0.138
	(0.007)	(0.092)	(0.007)	(0.085)	(0.004)	(0.050)
7 Up Reg.	0.069	0.237	0.064	0.220	0.037	0.128
	(0.002)	(0.130)	(0.002)	(0.121)	(0.001)	(0.070)
7 Up Diet	0.074	0.278	0.068	0.258	0.040	0.151
	(0.007)	(0.129)	(0.007)	(0.120)	(0.004)	(0.070)

Notes. Standard errors are reported in parentheses.

Source: Constructed by authors

Table 2.1 Definition and descriptive statistics of the variables in the sample

Variable	Definition	Mean	St. dev.	Min	Max
County Level					
Supermarket	Density of supermarkets and other grocery stores (per 1000 persons)	0.251	0.104	0.096	0.756
Convenience store	Density of convenience stores (per 1000 persons)	0.186	0.070	0.042	0.500
Fruit and veg. market	Density of fruit and vegetable markets (per 1000 persons)	0.044	0.053	0.000	0.435
Supercenter	Density of warehouse clubs and supercenters (per 1000 persons)	0.069	0.087	0.000	0.455
Full-service restaurant	Density of full-service restaurants (per 1000 persons)	0.954	0.309	0.285	3.665
Limited-service rest.	Density of limited-service eating places (per 1000 persons)	0.939	0.209	0.285	1.860
Median income	Median value of income level in each county (divided by 1000)	54046	11319	26523	84250
Property crime rate	Number of property crimes per 1000 persons	10.822	10.277	0.000	35.350
Violence crime rate	Number of violence crimes per 1000 persons	1.966	3.695	0.000	34.447
Population density	Number of persons per 1000 square miles in each county	1.130	2.213	0.004	12.338
Individual Level					
BMI	Body mass index	26.502	5.026	12.171	89.019
Age	Age in years	47.900	13.841	18.000	75.000
Children	Number of children	0.731	1.073	0.000	10.000
Education	Education level	5.076	1.000	1.000	6.000
Income	Income level	6.280	1.862	1.000	8.000
Female	1 if female	0.574	0.494	0.000	1.000
White	1 if race is White	0.884	0.320	0.000	1.000
Hispanic	1 if race is Hispanic	0.051	0.220	0.000	1.000
Black	1 if race is Black	0.031	0.172	0.000	1.000
Asian	1 if race is Asian	0.015	0.122	0.000	1.000
Married	1 if married	0.589	0.492	0.000	1.000
Smoke	1 if smoked at least 100 cigarettes in entire life	0.578	0.586	0.000	1.000
Drink	1 if drank any alcohol beverage in past 30 days	0.903	0.296	0.000	1.000
Activity	1 if do vigorous activity more than 10 minutes in a week	0.312	0.465	0.000	1.000
Retire	1 if retired	0.632	0.482	0.000	1.000

Table 2.2 Categories for metro counties and non-metro counties

Code	Description
Metro counties	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Non-metro counties	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area

Table 2.3 Econometric results - Full sample vs. Metro- sample vs. Non-metro sample.

Variable	Full sample		Metro- sample		Non-metro- sample	
Production Frontier	Coef.	Z-value	Coef.	Z-value	Coef.	Z-value
Age	0.135***	25.22	0.129***	22.34	0.139***	15.00
Children	0.012***	12.17	0.013***	12.54	0.020***	9.14
Education 1	-0.048***	-10.18	-0.031***	-5.90	-0.052***	-4.89
Education 2	-0.009***	-4.63	-0.006***	-2.81	-0.011***	-3.08
Income 2	-0.027***	-5.82	-0.043***	-9.15	-0.061***	-8.15
Income 3	-0.042***	-5.53	-0.075***	-9.52	-0.086***	-8.42
Income 4	-0.042***	-4.60	-0.094***	-10.04	-0.113***	-8.51
Female	-0.102***	-14.25	-0.114***	-13.99	-0.136***	-24.54
White	-0.010***	-2.90	-0.014***	-3.97	0.002	0.21
Black	0.046***	11.03	0.044***	10.93	0.034	1.58
Hispanic	0.016***	4.17	0.015***	3.89	0.007	0.68
Asian	-0.083***	-17.49	-0.086***	-17.06	-0.076***	-6.55
Married	0.006***	5.96	0.004***	3.72	0.012***	6.06
Smoke	0.040	1.00	-0.027***	-0.58	-0.075	-1.25
Drink	-0.427***	-10.44	-0.125***	-2.79	-0.059	-1.02
Activity	-0.169***	-3.07	-0.325***	4.89	-0.470***	-9.91
Retire	0.220***	15.71	0.253***	16.79	0.296***	13.60
Constant	2.983***	47.00	2.863***	44.58	2.840***	41.59
Determinants of Inefficiency						
Supermarket	-0.136	-0.88	-0.415	-1.12	-0.028**	-0.33
Convenience store	0.020	0.19	0.235	0.89	-0.091	-1.03
Fruit and veg. store	-0.548***	-2.62	-0.596	-0.88	-0.084	-0.39
Supercenter	0.570***	2.90	-0.197	-0.24	0.261*	1.83
Full-service restaurant	-0.200***	-4.21	-0.335***	-3.61	-0.123**	-3.96
Limited-service Rest.	0.121*	1.69	0.213*	1.89	0.070	0.94
Median income	-5E-06***	-6.40	-6E-06**	-5.66	-4E-06*	-2.48
Crime rate	0.001	0.90	0.001	0.96	0.002	1.39
Population density	-0.036**	-2.26	-0.058*	-1.72	-0.052	-0.21
Constant	-0.431***	-4.48	-0.453***	-3.36	-0.219**	-2.02
Distribution of *u* and *v*						
σ_u^2	0.152***	14.81	0.171***	10.69	0.111***	13.88
σ_v^2	0.013***	60.69	0.014***	56.00	0.013***	41.67
γ	0.920***	207.47	0.927***	154.50	0.899***	145.42
Log Likelihood	69938.864		49802.71		14648.18	
Observations	191837		135467		41545	

Note: State and year fixed effects are included in the model. Robust standard errors clustered at the county level are estimated via bootstrapping. Z-value are reported in the table.
*, **, *** represent the 10%, 5%, 1% significance level, respectively.

Table 2.4 Econometric results-metro counties

	Pop.>1 million		250,000<Pop.<1 million		Pop.<250,000	
	Coefficient	Z-Score	Coefficient	Z-Score	Coefficient	Z-Score
Supermarket	-0.113	-0.21	-2.853***	-2.73	-0.807	-1.06
Convenience store	-0.006	-0.01	1.643	1.43	0.661	0.89
Fruit and veg. store	-2.992**	-2.07	-0.068	-0.04	1.411	0.55
Supercenter	2.856	1.51	-1.650	-0.91	-0.569	-0.67
Full-ser. restaurant	-0.562**	-2.25	0.418	1.29	0.079	0.09
Limited-ser. rest.	0.648***	2.68	-0.256	-0.45	-0.174	-0.39
Median income	-5E-06***	-3.06	-3E-06	-0.71	3E-06	0.27
Crime rate	0.006*	1.89	0.001	0.53	0.004	0.52
Population density	-0.064	-0.88	-0.003	-0.01	-0.630	-0.39
Constant	-1.077***	-3.21	-0.437	-1.02	-0.387	-0.89

Note: State and year fixed effects are included in the model. Robust standard errors clustered at the county level are estimated via bootstrapping. *, **, *** represent the 10%, 5%, 1% significance levels, respectively. Pop.>1 million stands for counties in metro areas of 1 million population or more; 250,000<Pop. <1 million stands for counties in metro areas of 250,000 to 1 million population; Pop. <250,000 stands for counties in metro areas of fewer than 250,000 population. Estimated coefficients for consumers' characteristics are omitted for brevity.

Table 2.5 Econometric results-non-metro counties

	Pop.>2500, adjacent		Pop.>2500, not adjacent		Completely rural	
	Coefficient	Z-Score	Coefficient	Z-Score	Coefficient	Z-Score
Supermarket	-0.380**	-2.38	0.073	0.38	-0.324	-0.12
Convenience store	0.030	0.18	-0.038	-0.10	0.700	0.03
Fruit and veg. store	-0.434	-0.58	0.597	0.84	0.013	0.02
Supercenter	-0.137	-0.33	-0.166	-0.54	-0.519	-0.06
Full-ser. restaurant	-0.108**	-2.13	-0.067	-0.89	0.177	0.15
Limited-ser. rest.	0.268*	1.71	-0.141	-0.80	0.063	0.03
Median income	-2E-07	-0.07	-5E-06	-1.15	8E-05	0.02
Crime rate	0.005***	2.67	-0.002	-0.85	-0.009	-0.20
Population density	-0.890***	-2.74	-0.011	-0.01	-8.404	-0.16
Constant	-0.379***	-2.79	-0.050	-0.20	-0.438	-0.02

Note: State and year fixed effects are included in the model. Robust standard errors clustered at the county level are estimated via bootstrapping. *, **, *** represent the 10%, 5%, 1% significance levels, respectively. Pop.>2500, adjacent stands for counties with urban population of 2,500 or more, adjacent to a metro area; Pop.>2500, not adjacent stands for counties with urban population of 2,500 or more, not adjacent to a metro area; Completely rural stands for counties that are completely rural or less than 2,500 urban population, adjacent or not adjacent to a metro area. Estimated coefficients for consumers' characteristics are omitted for brevity.

Table 2.6 Rankings of weight production efficiency for New England counties during 2001-2010

Rank	State	County	Efficiency	Rank	State	County	Efficiency	Rank	State	County	Efficiency
1	MA	Suffolk	0.898	27	CT	New London	0.871	53	ME	Oxford	0.859
2	NH	Carroll	0.888	28	CT	New Haven	0.870	54	VT	Franklin	0.857
3	MA	Barnstable	0.886	29	NH	Merrimack	0.870	55	ME	Androscoggin	0.856
4	CT	Fairfield	0.886	30	VT	Washington	0.870	56	ME	Penobscot	0.856
5	MA	Norfolk	0.886	31	VT	Bennington	0.870	57	VT	Caledonia	0.856
6	RI	Washington	0.882	32	MA	Franklin	0.870	58	ME	Kennebec	0.855
7	RI	Bristol	0.882	33	NH	Belknap	0.870	59	ME	Piscataquis	0.855
8	RI	Newport	0.881	34	VT	Addison	0.870	60	ME	Aroostook	0.853
9	MA	Middlesex	0.880	35	ME	York	0.870	61	ME	Washington	0.851
10	MA	Cumberland	0.880	36	NH	Cheshire	0.869	62	ME	Somerset	0.845
11	VT	Grand Isle	0.879	37	RI	Kent	0.868				
12	CT	Litchfield	0.879	38	MA	Worcester	0.867				
13	ME	Lincoln	0.879	39	ME	Sagadahoc	0.867				
14	VT	Windham	0.878	40	NH	Sullivan	0.867				
15	MA	Hampshire	0.878	41	RI	Providence	0.866				
16	NH	Grafton	0.877	42	NH	Strafford	0.865				
17	ME	Hancock	0.877	43	VT	Lamoille	0.865				
18	VT	Chittenden	0.876	44	ME	Franklin	0.864				
19	NH	Rockingham	0.876	45	ME	Waldo	0.863				
20	MA	Plymouth	0.875	46	MA	Bristol	0.862				
21	CT	Tolland	0.874	47	CT	Windham	0.862				
22	ME	Knox	0.874	48	NH	Coos	0.861				
23	MA	Essex	0.873	49	MA	Hampden	0.861				
24	CT	Hartford	0.872	50	VT	Orange	0.861				
25	VT	Windsor	0.872	51	VT	Rutland	0.860				
26	NH	Hillsborough	0.871	52	VT	Orleans	0.860				

Table 3.1. Summary of Milk Product Characteristics.

Company/Brand	Price	Mark. Share	Fat	Lactose-Free	Size/Gallon
Dean Food/Garelick					
Garelick Farms 1	5.949	0.002	0	0	0.25
Garelick Farms 2	4.725	0.007	0	0	0.5
Garelick Farms 3	3.632	0.007	0	0	1
Garelick Farms 4	6.016	0.003	0.01	0	0.25
Garelick Farms 5	4.731	0.009	0.01	0	0.5
Garelick Farms 6	3.62	0.013	0.01	0	1
Garelick Farms 7	5.984	0.002	0.02	0	0.25
Garelick Farms 8	4.731	0.008	0.02	0	0.5
Garelick Farms 9	3.654	0.011	0.02	0	1
Garelick Farms 10	5.967	0.003	0.0325	0	0.25
Garelick Farms 11	4.735	0.007	0.0325	0	0.5
Garelick Farms 12	3.642	0.011	0.0325	0	1
Dean Food/Garelick F. o.t. M.					
Garelick Farms over the Moon 1	5.897	0.002	0	0	0.5
Garelick Farms over the Moon 2	5.917	0.001	0.01	0	0.5
Hood/Hood					
Hood 1	6.085	0.002	0	0	0.25
Hood 2	4.607	0.007	0	0	0.5
Hood 3	3.44	0.011	0	0	1
Hood 4	5.736	0.001	0.01	0	0.25
Hood 5	4.66	0.008	0.01	0	0.5
Hood 6	3.473	0.015	0.01	0	1
Hood 7	6.048	0.001	0.02	0	0.25
Hood 8	4.699	0.007	0.02	0	0.5
Hood 9	3.602	0.011	0.0325	0	1
Hood 10	5.636	0.001	0.0325	0	0.25
Hood 11	4.747	0.007	0.0325	0	0.5
Hood 12	3.654	0.013	0.0325	0	1
Hood/ Hood Lactaid					
Hood Lactaid 1	9.531	0.0005	0	1	0.25
Hood Lactaid 2	7.680	0.003	0	1	0.5
Hood Lactaid 3	7.625	0.002	0.01	1	0.5
Hood Lactaid 4	9.569	0.0003	0.02	1	0.25
Hood Lactaid 5	7.682	0.002	0.02	1	0.5
Hood Lactaid 6	7.604	0.001	0.0325	1	0.5
Hood/ Hood Simply Smart					
Hood Simply Smart 1	6.137	0.009	0.01	0	0.5
Hood Simply Smart 2	6.156	0.005	0.01	0	0.5

Private Label					
Private Label 1	5.375	0.001	0	0	0.25
Private Label 2	3.966	0.018	0	0	0.5
Private Label 3	2.843	0.065	0	0	1
Private Label 4	6.691	0.001	0	1	0.5
Private Label 5	5.238	0.0005	0.01	0	0.25
Private Label 6	3.849	0.021	0.01	0	0.5
Private Label 7	2.806	0.118	0.01	0	1
Private Label 8	5.208	0.003	0.02	0	0.25
Private Label 9	3.835	0.016	0.02	0	0.5
Private Label 10	2.817	0.076	0.02	0	1
Private Label 11	6.633	0.001	0.02	1	0.5
Private Label 12	5.391	0.002	0.0325	0	0.25
Private Label 13	3.836	0.019	0.0325	0	0.5
Private Label 14	2.836	0.096	0.0325	0	1
Private Label 15	6.564	0.0003	0.0325	1	0.5
Smart Balance/ Smart Balance					
Smart Balance 1	6.061	0.001	0	0	0.5
Smart Balance 2	5.908	0.001	0	1	0.5
Smart Balance 3	5.950	0.0002	0.01	0	0.5
Stonyfield Farm/Stonyfield Farm					
Stonyfield Farm 1	7.383	0.003	0	0	0.5
Stonyfield Farm 2	7.367	0.003	0.01	0	0.5
Stonyfield Farm 3	7.388	0.002	0.02	0	0.5
Stonyfield Farm 4	7.370	0.003	0.0325	0	0.5

Table 3.2. Demand Estimation Results

Variable	Mean Utility Mean	Mean Utility Standard Errors	Unobservables Mean	Unobservables Standard Errors
Price	-2.281***	(0.626)	-0.467*	(0.245)
Fat	-11.799**	(5.219)	-28.536**	(2.252)
Lactose-Free	0.960	(1.812)	1.511	(0.790)
Size	-2.789*	(1.479)	-0.618	(0.450)
Garelick Farms	-5.550	(3.395)	-4.201	(2.903)
Garelick Farms o. t. Moon	-7.110	(5.805)	-4.086	(4.028)
Hood	-5.076	(8.733)	-3.097	(9.224)
Hood Lactaid	-1.240	(2.761)	1.213	(4.701)
Hood Simply Smart	-4.343	(85.345)	-3.311	(52.119)
PLs	-4.114***	(1.115)	-6.220*	(3.717)
Smart Balance	-16.001*	(9.690)	-8.034	(4.983)
Constant	-10.477***	(4.117)	0.890	(1.901)
Month Fixed Effect			Yes	

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.3. Sample of Price Elasticities of Demand for Milk Products

Product	Garel. Farm 6	Garel. Farm 9	Hood 6	Hood 12	Hood Lact. 2	Hood Lact. 3	Private Label 3	Private Label 10	Private Label 14	Stonyfield Farm 1
Garelick Farms 6	-11.370	0.017	0.014	0.012	0.013	0.016	0.042	0.035	0.033	0.030
Garelick Farms 9	0.014	-11.920	0.013	0.011	0.011	0.016	0.041	0.035	0.032	0.030
Hood 6	0.018	0.019	-12.277	0.014	0.016	0.019	0.053	0.048	0.040	0.037
Hood 12	0.018	0.018	0.017	-11.976	0.014	0.019	0.051	0.045	0.039	0.033
Hood Lactaid 2	0.018	0.019	0.017	0.015	-11.525	0.019	0.048	0.046	0.041	0.038
Hood Lactaid 3	0.015	0.017	0.016	0.012	0.013	-10.715	0.045	0.041	0.035	0.030
Private Label 3	0.015	0.016	0.014	0.012	0.012	0.015	-9.521	0.037	0.033	0.030
Private Label 10	0.017	0.018	0.015	0.013	0.014	0.018	0.046	-9.753	0.037	0.031
Private Label 14	0.017	0.018	0.016	0.014	0.014	0.019	0.045	0.045	-10.432	0.031
Stonyfield Farm 1	0.015	0.016	0.014	0.013	0.013	0.017	0.045	0.039	0.032	-11.967

Table 3.4. Price, Marginal Cost and Lerner Index

Company/Brand	Price	MC	Price-MC	Own-price Ela.	Lerner Index
Dean Food/Garelick					
Garelick Farms 1	5.554	5.050	0.504	-11.604	0.091
Garelick Farms 2	5.476	4.962	0.513	-11.571	0.094
Garelick Farms 3	5.476	4.963	0.513	-11.352	0.094
Garelick Farms 4	5.464	4.951	0.514	-11.483	0.094
Garelick Farms 5	5.339	4.824	0.515	-11.237	0.097
Garelick Farms 6	5.356	4.833	0.523	-11.370	0.098
Garelick Farms 7	5.361	4.855	0.505	-11.134	0.094
Garelick Farms 8	5.351	4.838	0.513	-11.498	0.096
Garelick Farms 9	5.426	4.910	0.516	-11.920	0.095
Garelick Farms 10	5.417	4.899	0.518	-11.799	0.096
Garelick Farms 11	5.355	4.829	0.526	-11.657	0.098
Garelick Farms 12	5.381	4.862	0.519	-11.734	0.096
Dean Food/Garelick F. o.t. M.					
Garelick Farms o. t. Moon 1	5.390	4.869	0.521	-11.821	0.097
Garelick Farms o. t. Moon 2	5.479	4.948	0.531	-11.798	0.097
Hood/Hood					
Hood 1	5.456	4.934	0.522	-11.535	0.096
Hood 2	5.556	5.030	0.526	-11.612	0.095
Hood 3	5.803	5.287	0.516	-12.340	0.089
Hood 4	5.816	5.290	0.526	-12.229	0.090
Hood 5	5.818	5.299	0.519	-12.170	0.089
Hood 6	5.812	5.287	0.526	-12.277	0.090
Hood 7	5.847	5.328	0.519	-12.400	0.089
Hood 8	5.799	5.278	0.521	-12.617	0.090
Hood 9	5.852	5.339	0.513	-12.359	0.088
Hood 10	5.834	5.317	0.518	-12.490	0.089
Hood 11	5.649	5.133	0.515	-12.198	0.091
Hood 12	5.667	5.144	0.523	-11.976	0.092
Hood/ Hood Lactaid					
Hood Lactaid 1	5.665	5.156	0.510	-11.516	0.090
Hood Lactaid 2	5.663	5.149	0.514	-11.525	0.091
Hood Lactaid 3	5.130	4.611	0.519	-10.715	0.101
Hood Lactaid 4	4.902	4.377	0.525	-10.251	0.107
Hood Lactaid 5	4.753	4.225	0.528	-9.851	0.111
Hood Lactaid 6	4.842	4.322	0.520	-10.130	0.107
Hood/ Hood Simply Smart					
Hood Simply Smart 1	4.649	4.133	0.516	-9.483	0.111
Hood Simply Smart 2	4.664	4.139	0.525	-9.487	0.113

Private Label					
Private Label 1	4.554	4.013	0.541	-9.571	0.119
Private Label 2	4.533	3.991	0.542	-9.537	0.120
Private Label 3	4.548	4.007	0.541	-9.521	0.119
Private Label 4	4.581	4.039	0.542	-9.407	0.118
Private Label 5	4.546	4.003	0.543	-9.574	0.119
Private Label 6	4.530	3.982	0.548	-9.577	0.121
Private Label 7	4.603	4.056	0.548	-9.639	0.119
Private Label 8	4.669	4.116	0.553	-9.726	0.118
Private Label 9	4.633	4.092	0.541	-9.764	0.117
Private Label 10	4.669	4.118	0.551	-9.753	0.118
Private Label 11	5.173	4.634	0.539	-9.880	0.104
Private Label 12	5.234	4.682	0.552	-9.993	0.105
Private Label 13	5.390	4.851	0.540	-9.873	0.100
Private Label 14	5.444	4.904	0.541	-10.432	0.099
Private Label 15	5.794	5.277	0.517	-11.875	0.089
Smart Balance/ Smart Balance					
Smart Balance 1	5.649	5.148	0.502	-11.549	0.089
Smart Balance 2	5.553	5.052	0.501	-11.566	0.090
Smart Balance 3	5.578	5.084	0.494	-11.711	0.088
Stonyfield Farm/Stonyfield Farm					
Stonyfield Farm 1	5.801	5.298	0.503	-11.967	0.087
Stonyfield Farm 2	5.711	5.208	0.503	-12.042	0.088
Stonyfield Farm 3	5.708	5.203	0.505	-11.742	0.088
Stonyfield Farm 4	5.659	5.159	0.500	-12.036	0.088

Table 3.5. Estimation of Cost Function

Independent Variables Log(marginal cost)	(1)	(2)	(3)
Log(diesel)	0.257***	0.424***	0.425***
	(0.033)	(0.086)	(0.086)
Log(electricity)	1.925***	3.241***	3.241***
	(0.151)	(0.127)	(0.127)
Log(feed)	0.117***	0.117***	0.119**
	(0.026)	(0.018)	(0.047)
Log(size)	-0.526***	-0.512***	-0.512***
	(0.124)	(0.009)	(0.009)
Fat	-3.391***	-4.734***	-4.735***
	(0.503)	(0.412)	(0.413)
Constant	-3.319***	-6.079***	-6.093***
	(0.310)	(0.247)	(0.325)
Hood (Manufacturer Brand)	No	0.233***	0.233***
		(0.018)	(0.018)
Smart B. (Manufacturer Brand)	No	-0.063***	-0.063***
		(0.044)	(0.044)
PLs	No	-0.161***	-0.161***
		(0.036)	(0.036)
Stonyfield Farm (Organic)	No	0.492***	0.491***
		(0.044)	(0.043)
Month Dummy	No	No	Yes
Year Dummy	No	No	Yes
BIC	370.696	-1031.09	-938.506
R2	0.502	0.755	0.756

Table 3.6. Pass-through Rate Estimates

Company/Brand	Pass-through Rate
Dean Food/Garelick	
Garelick Farms 1	0.6353
Garelick Farms 2	0.6431
Garelick Farms 3	0.5668
Garelick Farms 4	0.6099
Garelick Farms 5	0.5989
Garelick Farms 6	0.6319
Garelick Farms 7	0.5821
Garelick Farms 8	0.5878
Garelick Farms 9	0.6241
Garelick Farms 10	0.6481
Garelick Farms 11	0.6275
Garelick Farms 12	0.6100
Dean Food/Garelick F. o.t. M.	
Garelick Farms o. t. Moon 1	0.6683
Garelick Farms o. t. Moon 2	0.5864
Hood/Hood	
Hood 1	0.6330
Hood 2	0.5941
Hood 3	0.6678
Hood 4	0.5608
Hood 5	0.6422
Hood 6	0.6530
Hood 7	0.6312
Hood 8	0.5540
Hood 9	0.6664
Hood 10	0.6019
Hood 11	0.5593
Hood 12	0.6582
Hood/ Hood Lactaid	
Hood Lactaid 1	0.6245
Hood Lactaid 2	0.6388
Hood Lactaid 3	0.6966
Hood Lactaid 4	0.6802
Hood Lactaid 5	0.6221
Hood Lactaid 6	0.6520
Hood/ Hood Simply Smart	

Hood Simply Smart 1	0.6737
Hood Simply Smart 2	0.6328
Private Label	
Private Label 1	0.6876
Private Label 2	0.5886
Private Label 3	0.6371
Private Label 4	0.6005
Private Label 5	0.5611
Private Label 6	0.6436
Private Label 7	0.5746
Private Label 8	0.6165
Private Label 9	0.6290
Private Label 10	0.6208
Private Label 11	0.6305
Private Label 12	0.6289
Private Label 13	0.5793
Private Label 14	0.5746
Private Label 15	0.5782
Smart Balance/ Smart Balance	
Smart Balance 1	0.6392
Smart Balance 2	0.5862
Smart Balance 3	0.6231
Stonyfield Farm/Stonyfield Farm	
Stonyfield Farm 1	0.6502
Stonyfield Farm 2	0.6134
Stonyfield Farm 3	0.6536
Stonyfield Farm 4	0.6552